Essays on the Allocation of Scarce Resources among Competing Ends

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Abstract

The first chapter of this dissertation evaluates changes in fuel procurement practices by coal- and natural gas-fired electricity generating plants in the United States following state-level legislation that ended cost-of-service regulation. I construct a detailed dataset that links confidential, shipment-level data on the price of virtually all of the fuel delivered to coal- and gas-fired electricity plants in the United States from 1990-2009, with plant-level data on operations and regulatory status. I find the price of coal drops by 12% at deregulated plants relative to matched plants that were not subject to any regulatory change, whereas there was no relative drop in the price of gas. I show how my results lend support to theories of asymmetric information between generators and regulators, regulatory capture, and capital-bias as important sources of distortion under cost-of-service regulation.

The second chapter analyses changes in the cost of generating electricity following the introduction of regional wholesale electricity markets. I use proxy methods based on Olley and Pakes (1996); Levinsohn and Petrin (2003) to estimate fuel-specific production functions, and construct the Olley-Pakes productivity index to decompose costs in to within-plant productivity and allocative efficiency changes. I then apply a potential outcomes framework to the derived productivity estimates, allowing the construction of counterfactual costs that explicitly account for permanent differences between market

and non-market areas and common transitory shocks. I find that the introduction of market-based dispatch methods has reduced fossil-fuel production costs by upwards of 15%.

The third chapter is based on joint work with Roland Fryer and Jorg Spenkuch. We develop a Roy model in which individuals sort into peer groups based on comparative advantage. Two key results emerge: First, when comparative advantage is the guiding principle of peer group organization, the effect of moving a student into an environment with higher-achieving peers depends on where in the ability distribution she falls and the effective wages that clear the social market. As a result, linear in means estimates of peer effects are not identified. We show that the model's testable prediction in the presence of this confounding issue is borne out in two data sets.

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To my family.

Nothing teaches you about opportunity cost quite like graduate school in economics.

Chapter 1

When Does Regulation Distort Costs? Lessons from Fuel Procurement in US Electricity Generation

1.1 Introduction

What determines whether government policy intended to correct a market failure improves social welfare, or ultimately causes more harm than the problem it was intended to ameliorate? In this paper I identify three leading potential mechanisms from the theoretical literature seeking to answer this question, and measure their importance in contributing to distortions in fuel procurement arising from cost-of-service regulation of U.S. electricity generation.

To do so, I develop a model of a regulated monopolist who may reduce the price paid for fuel by exerting costly effort (more intensive search, negotiation, etc.) that is not directly observed by the regulator. The regulator has discretion to allow "prudently incurred" costs to be recovered, and the fixed cost of effort is covered by receiving a rate of return on the capital value of the plant that exceeds the cost of capital. The "Averch-Johnson Effect" (Averch and Johnson (1962)) predicts that this compensation scheme leads firms to adopt economically inefficient production techniques that are capital-biased. It also becomes impossible to induce efficient cost-reducing effort when the regulator is unable to observe both effort and the cost of this effort (Laffont and

Tirole (1986, 1993)). Finally, fuel prices are predicted to exceed those prevailing under competition when special interest groups (such as coal producers) influence the regulator's decision on which costs to allow (Stigler (1971); Peltzman (1976); Grossman and Helpman (2002)).

I compare the importance of the mechanisms hypothesized by these theories at natural gas- and coal-fired electricity generating facilities following the end of cost-of-service regulation in states that passed electricity industry restructuring legislation. By virtue of the need to transmit via public thoroughfares, the production and sale of electricity has historically been regulated by state or municipal governments in the United States (Stigler and Friedland (1962); Jarrell (1978)). When not owned by the government, electricity providers have typically taken the form of vertically-integrated Investor-Owned Utilities ("Utilities" or IOUs). IOUs own the generating plants, the transmission network, and exclusive licenses to sell electricity in their respective service areas. In the mid to late 1990's, state-level initiatives sought to restructure the electricity industry by transforming the rate-regulated IOUs in to participants in a competitive market guided by private investment, procurement, and production decisions. This required breaking up utilities so that owners of the transmission network could not favor their own plants in the face of lower-cost competition. This was often accomplished through divestiture, in which IOUs sold off their generating assets or transferred them to unregulated affiliates. Once divested, power plant operators' costs are no longer subject to oversight by the state Public Utility Commission. Although all states had at least held hearings to consider restructuring reforms by 2000, the California energy crisis put a halt to any legislation that had not already passed. As a result, the regulation of electricity generators varies dramatically across states, with over half of states virtually untouched by any reform.

To measure changes induced by this deregulation, I construct a panel on the operations, fuel costs, and regulatory status of all gas- and coal-fired electricity generating facilities in the lower 48 states, responsible for roughly two-thirds of U.S. electricity generation.[1] Although many plants initially ceased reporting costs following divestiture–as is standard when cost-of-service rules end–the Department of Energy's Energy Information Administration asserted its jurisdiction to collect data on fuel prices at deregulated plants beginning in 2002. This is the first study

[1]"Gas" and "Natural Gas" both refer to a gaseous mixture of hydrocarbons (mostly methane) extracted from underground deposits, are used interchangeably.

to evaluate the impact of deregulation on costs using detailed, restricted-access data from the post-divestiture period in U.S. electricity generation.

I employ a matched Differences-in-Differences (DID) estimator in the spirit of Heckman, Ichimura, Smith, and Todd (1998) to compare fuel prices and sulfur regulation compliance strategies at similar divested and non-divested plants in close geographical proximity. The estimation strategy relies on the assumption that fuel purchasing opportunities are identical between "treatment" and "control" facilities. Close proximity is therefore a critical element of the estimation strategy because coal transportation costs are substantial, and have changed over time. I find that divested plants reduce the price paid for coal by 12% relative to a counterfactual scenario in which their operations had continued under cost-of-service regulation.

A small fraction of this gain may attributed to the fact that divested generating units have been far more likely to have switched to cheaper, low-sulfur sub-bituminous coal.[2] The opposite is true of regulated generating units, which have disproportionately installed "scrubbers" as a means of compliance with sulfur emission regulations. Since scrubbers are enormously expensive pieces of equipment (~$400/kW of capacity), the fact that rate-regulated units would opt for more capital-intensive methods to achieve compliance with environmental regulations is consistent with the hypothesis of Averch and Johnson (1962).

The drop in the cost of coal following divestiture does not reflect the universal inefficiency of regulation. Instead, I find that divestiture had no impact on the price of fuel paid by gas-fired generators. These plants were commonly owned with coal-fired units by monopolistic IOUs, and were subject to the same change in regulatory oversight. Differences in the markets for natural gas and coal lend support to agency-based theories that emphasize the role of asymmetric information between firms and regulators as a source of distortion under regulation. While gas is a homogeneous commodity traded in regional markets with transparent prices, the market for coal is dominated by confidential bilateral contracts. In addition, shipping from mines is costly and plants must be specifically tuned to the heterogeneous characteristics of the coal being burned. Regulators therefore have less information on a coal-fired plant's purchasing opportunities, and

[2]Coal is classified by 'rank', which refers to the purity of energy concentrated over millions of years of exposure to heat and pressure. In decreasing order of energy content, they are: Anthracite (mostly in PA), Bituminous (Central Appalachia), Sub-bituminous (WY, CO, UT), and Lignite (TX). About 90% of coal burned for electricity generation in the United States is Bituminous or Sub-bituminous.

operators may justify expenses based on idiosyncrasies of their location and equipment. It is clear, however, that these justifications become less important when generators become the residual claimants of cost savings through divestiture.

To evaluate the importance of regulatory capture on distorting procurement decisions, I confine my analysis to the set of plants that were burning coal sourced in-state during the pre-divestiture period. Coal producers are hypothesized to have greater influence over regulators in the states in which their mines (and jobs) are located. I find that divested facilities in these areas increase their out-of-state purchases by about 25% relative to matched non-divested facilities in coal-producing states, suggesting that regulation was an impediment to efficient procurement. I also find evidence suggesting that local coal has had some success in protecting their operations, as price reductions in these areas are mostly confined to plants that switched to burning low-sulfur coal.

I then connect my data on coal purchases to detailed data on mining cost determinants in the counties of origin. This allows me to decompose the extent to which these changes are driven by a reallocation of rents between mines and utilities, as opposed to real social welfare gains. I find that divested plants buy coal from mines with substantially lower extraction cost profiles: the mined coal seams are about 30% thicker and 50% closer to the surface than coal purchased by matched facilities. In total, divested plants purchase coal that requires $\sim$ 25% less labor to extract from the ground at mines that pay 5% higher wages.

Aside from any conclusions that may be drawn regarding the wider debates on the merits of government intervention in the economy,[3] the sheer scale of the coal-fired electricity sector makes these results of independent interest. Over 40% of electricity in the United States is derived from coal, and fuel accounts for about 80% of variable costs (Fabrizio, Rose, and Wolfram (2007)). A 12% reduction in fuel prices at the coal-fired facilities that have already been divested amounts to about one billion dollars per year. These facilities account for roughly one quarter of U.S. coal-fired generating capacity; the remaining facilities have not undergone any major changes in regulatory structure.

[3] A form of cost-of-service has recently been implemented in health care under the "80/20 rule" of the Affordable Care Act. This rule requires that insurance companies reimburse their customers for any revenues exceeding a set percentage above medical expenditures. As opposed to regulation in the electricity sector, in which variable costs are simply passed through, this rule means that insurance companies can only raise their profits by spending more on medical care. My results suggest the notorious opacity of costs and political activity in this sector does not bode well for the anticipated cost-savings from recent health care reform legislation.

The structure of the paper is as follows: in the next section I describe the process of divestiture in the United States, and the institutional details that will facilitate estimation. The third section frames the potential sources of regulatory inefficiency with a model of regulatory oversight that captures the hypothesized mechanisms in a unified framework. The fourth section details the estimation strategy, and the fifth section describes the data that I will bring to bear on the question. The sixth and seventh sections discuss the results and the associated welfare gains. The final section concludes.

1.2 Background on the U.S. Electricity Industry

Operations under Cost of Service Regulation

The market for electricity was chaotic and competitive in its early years due to duplicative, non-exclusive franchises granted by municipalities (Jarrell (1978)). At the turn of the 20^{th} century, improvements in economies of scale of generation and transmission led to widespread consolidation in the industry. State governments responded to this consolidation by asserting themselves over municipalities to regulate the operations of electricity companies in their respective states. Under the subsequent form of regulation, utilities have been granted exclusive licenses to sell electricity in their service territories in exchange for being subject to oversight of their operations and the rates they are permitted to charge customers. IOUs are guaranteed recovery of 'prudent' costs incurred, as well as a pre-determined rate of return on the value of the utility's capital base. All major investments (such as building new generation assets or installing major abatement equipment for use with existing units) can only be undertaken with the approval of the state's Public Utility Commission. The prices an IOU is permitted to charge are determined during 'rate hearings'. These costly, politically charged affairs entail an intensive audit of the utility's costs, operations, and demand projections in order to justify a change in the pricing formula for electricity. Rate hearings may be requested by the utility, or may be automatically triggered when profits exceed a predetermined threshold.

Kahn (1971) argues that the regulatory lag induced by a rate hearing leads many utilities to reduce costs between adjustments so as to reap profits during periods of fixed output price. After oil price spikes in the 1970's, many state commissions allowed IOUs to implement automatic pass-through clauses for fuel costs since intermittent rate cases could not keep up with the rise in the IOU outlays.[4] Once the adjustment formula is set, IOUs are guaranteed recovery of their fuel costs without further oversight. Since IOUs operate exclusively in their service territory, it is not possible for consumers to punish inferior procurement practices by switching to a lower cost producer.

There are two additional types of facilities that deserve mention. An early effort to reduce the cost of electricity during the Carter Administration led to the Public Utility Regulatory Policy Act of 1978 (PURPA). PURPA made it easier for non-utility generating facilities to sell power to regulated entities in an attempt to remove barriers to entry in the industry. This was followed by the Energy Policy Act of 1992, which sought to remove some of the obstacles non-utilities faced when seeking transmission service from the IOUs who owned the wires. These reforms stimulated limited entry from non-utility generators, mostly co-generating facilities that also provided steam for industrial purposes (Joskow (2005)).[5]

The final class of operators are federal, municipal, and cooperative organizations. These organizations produce about 20% of the nation's electricity (mostly in rural areas), and have made up about 20% of U.S. coal-fired capacity since at least 1990. Public Utility Commissions do not have jurisdiction to regulate these entities since they are owned either by the government or their members. Facilities owned by either non-utilities or not-for-profits were not subject to divestiture, and therefore do not experience operational or regulatory changes during the period of study.

Restructuring and Divestiture

In spite of the successful deregulation of U.S. telecommunications (Olley and Pakes (1996)), airlines (Kahn (1987, 1988); Ng and Seabright (2001)), railroads (McFarland (1989); Ellig (2002)), and trucking (Rose (1987)), electricity was thought to be different. The fact that vertically integrated utilities owned both the generation assets and the wires meant that a deregulated firm would be

[4]Gollop and Karlson (1978), and Baron and Bondt (1979) provided early theoretical analysis on how these changes are likely to distort IOU procurement decisions by reducing the incentive to lower costs, as well as make utilities less likely to switch to lower cost fuels when switching costs require commission approval, but continuing to burn uneconomical fuel is costless to the utility. Kaserman and Tepel (1982) find evidence in favor of these hypotheses.

[5]Less than 2% of coal-fired capacity belong to this class of power plants. The mid-2000's saw more substantial entry in the form of gas-fired non-utility generators.

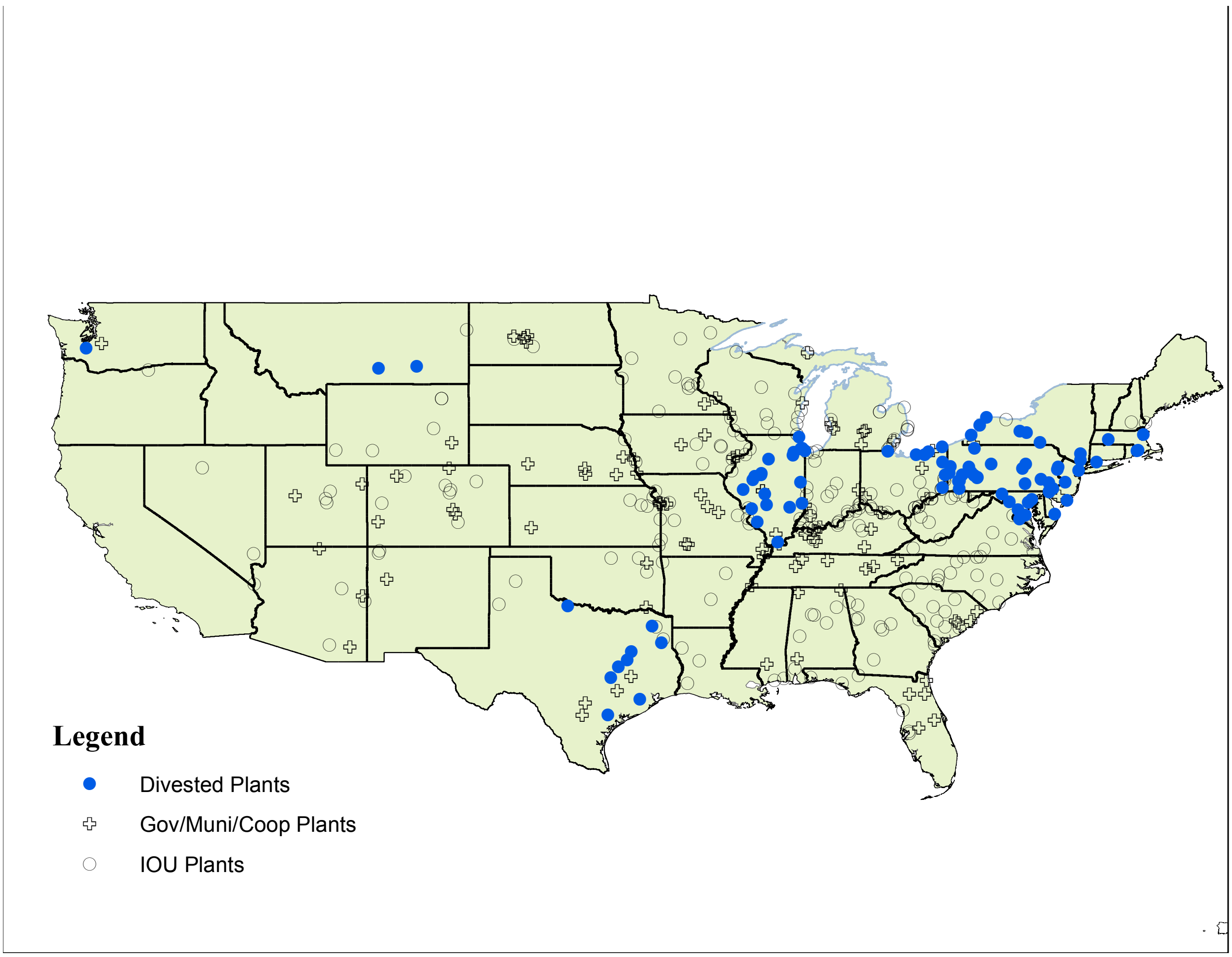
able to shut out competition from other producers. Markets in electricity could also be vulnerable to the exercise of market power since electricity production must match demand in every moment in time–the impossibility of storage means that a firm can unilaterally withhold capacity to drive up prices with impunity in a free market with high fixed costs of entry.

Joskow and Schmalensee (1988) was groundbreaking in that their evaluation of the electricity industry confronted these challenges directly, and suggested a set of policy options that would facilitate the transition to a restructured market. Among these policies was that vertically-integrated IOUs divest their generation assets to prevent owners of transmission networks from favoring their own plants. Instead, generators would be required to bid their capacity in day-ahead and real-time auctions, and would only be dispatched if their bid was below that of the marginal unit required to meet demand. This change transferred control of transmission networks to independent system operators in order to become participants in regional markets. Once divested, plant operators bear the full cost of their procurement decisions. Units that purchase relatively expensive fuel would be forced to raise their bids to break even in wholesale markets, and therefore become less likely to be called upon to operate.

Figure 1.1 shows the geographic distribution of these reforms with respect to coal-fired electricity stations in the United States that report fuel deliveries between 1990 and 2009.[6] Although divestitures were required of all IOU generating assets in states passing legislation, it is clear that neither coal-fired plants nor restructuring reforms were randomly spread across the country. Almost all coal production and consumption occurs to the east of the Rocky Mountains. At the time many coal-fired plants were built, most coal consumed by electric facilities in the United States was the high-sulfur, bituminous variety from the central Appalachian mountains and Illinois basin. In spite of the high cost of shipping coal relative to transmitting the derived power by wire, the establishment of exclusive service areas by IOUs ensured local utilities would not be competed out of the market by producers in the Ohio River Valley. This is one source of the price differential in electricity across areas that motivated restructuring legislation. Another major driver of restructuring legislation was the gap between retail and industrial electricity prices

[6]States that restructured, but do not have coal-fired generating assets reporting cost data include California, Washington, DC, Maine, and Rhode Island. New Hampshire introduced retail choice, but did not require divestiture of generating assets. A more detailed discussion of the state-by-state history of divestitures can be found in Data Appendix A.

Figure 1.1: *Coal-Fired Plants in The United States, 1990-2009*



(White (1996) and Joskow (1996)). States with larger gaps were more likely to restructure due to the perception that retail consumers were getting a raw deal relative to industrial buyers.

Restructuring legislation was first passed in the Northeastern states and California in the mid-1990s. The movement had gained sufficient momentum by 1998 that every state in the union had at least held hearings on the prospective gains from deregulation (Fabrizio, Rose, and Wolfram (2007)). This momentum dissipated quickly in the wake of the California electricity crisis of 2000-2001, leading several states who had made significant progress in the direction of restructuring to delay or cancel planned reforms (Joskow (2005)). No state has passed restructuring legislation since this time: fairly or not, restructuring is popularly associated with the spectacular failure in California, and a lack of significant offsetting benefits to consumers (Kwoka (2008)).[7] As noted by Joskow (2006), "Even the Cato Institute has lost patience with competitive reforms in electricity and appears to see merit in returning to the good old days of regulated vertically integrated utilities (Van Doren and Taylor (2004))."

That said, the states that had already restructured before the California crisis have not returned to the model of vertically-integrated IOUs. The perils of liberalized electricity markets have received significant scrutiny in the wake of the California electricity crisis (Borenstein, Bushnell, and Wolak (2002); Borenstein (2002); Bushnell, Mansur, and Savaria (2007); Mansur (2001, 2008)), and adjustments have been made to promote wholesale electricity markets that function reasonably well (Mansur and White (2012)). Recent work has also shown that restructuring is associated with more productive nuclear generating facilities (Davis and Wolfram (2012)), and declines in labor and non-fuel costs (Fabrizio, Rose, and Wolfram (2007)).[8] The market for electricity in the United States is therefore characterized by a patchwork of regulatory structures that are separated by state borders and/or historical service area boundaries.

[7]Borenstein, Bushnell, and Wolak (2002) find that the price of electricity would have tripled between 1998 and 2000 based on rising input costs alone. Although there were a number of factors that contributed to the crisis (including the exercise of market power), it was most certainly exacerbated by the fact that retail prices were fixed while wholesale prices were skyrocketing. This led generators to withhold capacity due to doubts of receiving compensation, not the exercise of market power. See Joskow (2001) for a detailed discussion of the history of the California electricity crisis.

[8]Fabrizio, Rose, and Wolfram (2007) as well as concurrent work by Chan, Fell, Lange, and Li (2012) define treatment as the time between law passage and divestiture because post-divestiture data on costs has not been utilized prior to this study. For work on incentives to invest in new capacity in restructured markets, see Bushnell and Ishii (2007), Ishii and Yan (2004), and Ishii and Yan (2007).

1.3 Sources of Regulatory Imperfection

To explore the possible mechanisms that can explain changes in the price of inputs following deregulation, it is helpful to consider the main hypotheses posed in the theoretical literature on regulatory imperfection. To do so I consider a setting in which a firm can reduce the price paid for inputs by exerting cost-reducing effort. After deriving the optimal behavior in the absence of regulation, I introduce standard rate-of-return (or "cost-plus") regulation, in which the regulator has discretion to approve capital investments and "prudent" variable costs. In a key departure from the agency literature, I leave the regulator's objective function unspecified. Rather than derive the optimal policy for the regulator, I am instead interested with how regulation affects the set of *feasible* policies. The reason for this approach is two-fold: it is sufficiently flexible to allow for consideration of different theories of regulatory inefficiency in a common framework, and it results in a set of hypotheses that can be taken to the data on firm behavior without having already assumed the nature of the regulator's objective.

Suppose generating facilities produce electricity by combining fuel (F) and capital (K) according to the quasiconcave production function $G(F,K)$–labor is a small share of generation costs and is ignored. Let p denote the per-unit compensation received by plant operators, whose determination will depend upon the regulatory environment. Given this price, plants face the inverse demand function $p = p[G(F,K)]$. For simplicity, assume a constant elasticity of demand, and denote the inverse price elasticity of demand $\eta = -\frac{G(F,K)}{p[G(F,K)]}\frac{dp}{dG}$, with $0 \leq \eta < 1$.[9] Suppose plants must exert managerial effort to solicit bids, negotiate contracts, etc. and that this effort reduces the price paid for coal according to $c = \beta - e$ where $e \in [0, \beta]$. Effort is itself costly, and reduces profits according to a convex function $\psi(e)$, $\psi'(e) > 0$, $\psi''(e) > 0$.

First, consider the behavior of the plant in the absence of regulation. Let $R = p[G(F,K)]G(F,K)$ denote total revenues when the manager considers the effect of output on price. The plant manager takes the rental rate of capital, r as given, and chooses effort and inputs to maximize

$$\max_{e,F,K} R - (\beta - e)F - rK - \psi(e) \tag{1.1}$$

[9] Sufficient conditions for a maximum will hold so long as the demand function is not so convex as to reverse the quasiconcavity of revenues with respect to inputs.

Assuming that price is sufficiently high to cover the fixed costs of effort, we have the standard first order conditions

$$\begin{aligned} [e]: & \quad \psi'(e) &= F \\ [F]: & \quad (1-\eta)pG_F &= (\beta - e) \\ [K]: & \quad (1-\eta)pG_K &= r \end{aligned}$$

The optimal effort equates the marginal cost of effort to the marginal benefit: a reduction in the cost of every unit of coal purchased. When the plant takes price as given, marginal revenue is equal to price (i.e. $\eta = 0$ from the firm's perspective), and standard optimality conditions for inputs equate marginal cost to value marginal product. It is worth noting the effect that market power has on input costs in this scenario. Since a monopolist will restrict output to raise price, the reduced demand for inputs implies less effort will be exerted to reduce input costs than in a competitive market.[10] Input costs in a deregulated market therefore depend on the ability of firms to exert market power. Let the triple (e^*, F^*, K^*) denote the effort and input demand in a competitive, deregulated market.

Next, suppose the firm is regulated on a cost-of-service basis known as "cost-plus." This does not imply that firms are (directly) rewarded for higher coal prices. Instead, variable costs are reimbursed only if the regulator deems them "prudent" and the plant receives a rate of return $s > r$ on its capital stock, or "rate base" that exceeds the cost of capital. The regulator is unable to directly observe cost-reducing effort, and instead decides whether or not to allow fuel expenditures based only on the reported price, c. Let $\theta(\beta - e)$ denote the probability that the regulator allows recovery of costs c. The firm therefore maximizes profits subject to the constraint that revenues are no greater than allowed costs:[11]

$$R \leq \theta(\beta - e)[\beta - e]F + sK$$

[10] Following Hicks (1935), the tendency for monopolists to have costs that exceed those prevailing under competition has been referred to as "the quiet life of the monopolist."

[11] Joskow (1974) argues that while regulators may use this constraint for setting nominal prices at formal rate hearings, firms are actually able to earn any rate of return so long as prices are not rising during intermediate periods. Jha (2012) extends this intuition in a model in which excess profits are confiscated, but imprudent expenditures are punished, inducing a form of risk aversion among regulated utilities. The widespread adoption of automatic fuel adjustment clauses in the late 1970's effectively re-coupled revenues and costs in the manner implied by the rate of return constraint. Imprudent costs may be rejected in the spirit of Jha (2012) through $\theta(\beta - e)$.

Thus the term "cost-plus": the revenues the firm can raise are equal to its prudently incurred variable costs, plus a guaranteed "fair rate of return" paid to capital. To focus attention on cost reduction, it is assumed that the regulator is perfectly able to observe and dictate quantities conditional upon costs.[12] This yields the Lagrangian and first order conditions

$$\mathcal{L} = \max_{e,F,K} R - (\beta - e)F - rK - \psi(e) + \lambda\{\theta(\beta - e)[\beta - e]F + sK - R\} \tag{1.2}$$

$$\begin{aligned}
[e]: \quad & \psi'(e) && = F\{1 - \lambda[\theta(\beta - e) + [\beta - e]\theta'(\beta - e)\} \\
[F]: \quad & (1-\eta)pG_F && = \frac{[1 - \lambda\theta(\beta - e)]}{(1-\lambda)}(\beta - e) \\
[K]: \quad & (1-\eta)pG_K && = r - \frac{\lambda}{(1-\lambda)}[s - r]
\end{aligned}$$

The binding revenue constraint and sufficient second order condition for a maximum imply $0 < \lambda < 1$.[13] Capital-bias is expressed clearly by assuming for a moment that the regulator approves all variables costs ($\theta(c) = 1 \,\forall\, c$). Instead of equating the relative marginal product of capital to the relative price, cost-plus recovery implies

$$\frac{G_K}{G_F} = \frac{r}{(\beta - e)} - \frac{\lambda}{(1-\lambda)}\frac{s-r}{\beta - e} < \frac{r}{(\beta - e)}$$

This is the seminal hypothesis of Averch and Johnson (1962): cost-plus regulation leads to economically inefficient capital-biased production, also called "gold-plating" and "rate-base padding"[14]. When cost recovery is guaranteed regardless of c, it is also clear that fuel prices are inefficiently high. This is because allowed revenues are directly tied to costs through the revenue constraint. While the plant bears the full cost of search effort, it only reaps benefits at rate $(1-\lambda)$.[15] One strategy is to decouple revenues from costs via "yardstick competition" (Shleifer

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[12]This is equivalent to defining the analogous probabilities of approval for fuel and capital as unity at the quantities desired by the regulator, and zero otherwise.

[13]The determinant of the bordered Hessian of (1.2) is positive when $\lambda < 1$ and revenues are not too concave.

[14]See Baumol and Klevorick (1970) for a more complete treatment, and Berg and Tschirhart (1988) (chapter 9) for a discussion of the subsequent literature on the "Averch-Johnson effect."

[15]If we instead assumed that the regulator could fully compensate the firm for effort, effort would be efficient conditional upon quantities, but quantity would still inefficiently low because the plant anticipates the effect of output on price.

(1985)). Under yardstick competition, the allowed output price is tied to the realized costs of *other* producers–thereby effectively setting λ and η to zero.

In the agency-theoretic approach, the regulator removes the unconditional guarantee of recovered costs in order to induce the plant to undertake the desired level of cost reduction effort and production. This is a relatively straightforward task when there is no uncertainty on intrinsic costs, β (i.e. the cost of fuel when no effort is exerted): the regulator approves the costs that maximize her objective function, and denies compensation otherwise.[16] The plant's best response is to comply with the regulator's wishes so long as the resulting profits are non-negative.

Of course, potential costs are often unobserved by the regulator, who makes decisions in the context of political pressure. Thus the interaction between regulators and firms has become a key area of interest in principal-agent theory (Baron and Myerson (1982); Laffont and Tirole (1986) and meticulously detailed in Laffont and Tirole (1993)). The workhorse model of modern political economy (Grossman and Helpman (2002)) adopts the principal-agent framework, and considers the influence of special interest groups as an argument in the regulator's objective function. From the plant's perspective, the common theme of these models is that the probability of recovering expenses depends in some way on reported costs. In choosing a profit-maximizing level of effort, the firm trades off the direct reduction of allowed revenue due to lower costs, and the increased probability of having costs allowed.

In the case of asymmetric information, the regulator must adopt a strategy of approving costs without observing effort or intrinsic costs. Suppose β can take on any value on the interval $[\underline{\beta}, \overline{\beta}]$ with some positive probability. Let $\underline{c}$ denote the costs realized when firms with intrinsic costs $\underline{\beta}$ exert optimal effort $e^*(\underline{\beta})$, and similarly for $\overline{c}$. While it is possible for the regulator to induce efficient outcomes over some range of β, this becomes infeasible as the unobserved heterogeneity grows sufficiently large so that it is no longer possible to punish higher costs while preserving solvency.

To see this, first note that the efficient level of effort in the first-best world is decreasing in

[16] If we consider only differentiable strategies, the first best outcomes of (1.1) are achieved when the regulator approves effort e^* with certainty, and the probability of cost allowance at the optimum changes according to $\theta'(\beta - e^*) = -\frac{\theta(\beta-e^*)}{(\beta-e^*)}$. This neutralizes the effect of the rate of return constraint by increasing the probability of allowed costs one-for-one with cost-reducing effort–a zero net revenue effect.

intrinsic costs, that is $\frac{de^*}{d\beta} < 0$.[17] As a result, optimal costs are increasing with intrinsic costs, $\frac{dc^*}{d\beta} > 0$. This makes sense, for otherwise we would have the perverse scenario in which firms with higher costs are producing more than those with lower costs. Similarly, applying the envelope theorem to (1.2) when differentiating profits with respect to β implies that profits of an operating plant are strictly declining as intrinsic costs rise.

Suppose the regulator approves $\theta(c) = 1$ for $c \leq \underline{c}$, with $\theta'(c) = -\frac{\theta(c)}{c}$ for $c \geq \underline{c}$. This is a feasible strategy to induce efficient search so long as profits remain non-negative. However, for fixed $\underline{\beta}$, as $\overline{\beta}$ grows large, there will eventually be a region of β in which the optimal policy does not allow the plant to cover its costs, and is forced to shut down. It is important to note that this is due to the variance of unobserved heterogeneity, not the levels of costs. When intrinsic costs are high, but observed, it is perfectly possible for the regulator to approve costs at the efficient level of effort. This is a classic result in principal-agent theory, typically proven in circumstances in which the regulator aims to maximize the sum of consumer surplus and profits. The point here is that efficient effort is impossible to induce under *any* regulator objective function when unobserved heterogeneity is sufficiently large.

The inefficiency associated with regulatory capture is also straightforward to demonstrate. Suppose the local coal mines exert some influence over the regulator's decision-making. In this case, the regulator approves fuel costs according to $\theta(c, b)$ where b represents the influence of the mines, perhaps via campaign contributions as in Grossman and Helpman (2002). In this case we can express the effect of this influence on allowed costs as $\frac{\partial\theta}{\partial b} > 0$; $\frac{\partial^2\theta}{\partial b \partial c} \geq 0$ – contributions raise the probability of allowing high fuel costs, and reduce the punishment for marginally reducing effort.[18] To show how increased mining influence affects the cost-minimizing effort exerted by plants, suppose the regulator is initially inducing optimal effort with $\frac{\partial\theta}{\partial c} = -\frac{\theta(\beta - e^*, b)}{(\beta - e^*)}$ and consider the effect of a marginal rise in influence on search effort. Accounting for political influence via

[17] This is shown by differentiating the first order conditions of (1.1) with respect to β while noting input demand is a function of fuel price. The input demand conditions yields the standard $\frac{\partial F}{\partial c} = \frac{R_{KK}}{R_{KK}R_{FF} - R_{FK}^2} < 0$, by the assumed quasiconcavity of revenue. Differentiating the optimal effort condition yields $\frac{de^*}{d\beta} = \frac{\frac{\partial F}{\partial c}}{\frac{\partial F}{\partial c} + \psi''(e^*)}$. This implies optimal effort is decreasing in intrinsic costs so long as the convexity of the effort function is greater than the drop in fuel demand arising from higher fuel prices. This follows from the assumption that the revenue function is not too concave in order for the solution to (1.1) to be a maximum.

[18] In fact, the necessary assumption is that $\frac{\partial^2\theta}{\partial b \partial c}$ not be so negative as to reverse the direct effect of $\frac{\partial\theta}{\partial b}$.

$\theta(c,b)$ in (1.2), differentiation of the analogous first order condition for effort with respect to b and substituting in for the initial policy yields

$$\frac{de^*}{db} = -\frac{F\lambda[\frac{\partial\theta}{\partial b} + (\beta - e^*)\frac{\partial^2\theta}{\partial c\partial b}]}{\psi''(e^*) + \frac{\partial F}{\partial c}}$$

The denominator is positive by the same condition that implies $\frac{de^*}{d\beta} < 0$. Thus an increase in political influence leads to a decrease in cost-reducing effort, and higher fuel prices.

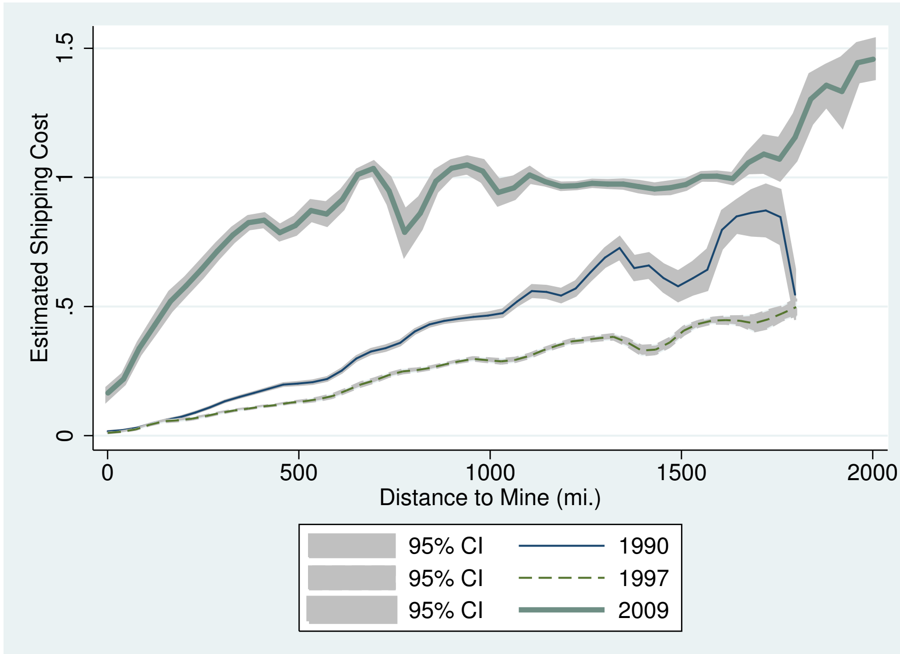
We have therefore derived a core set of predictions to test against the data. The price of fuel is expected to remain constant after divestiture when determinants of cost are readily observable by the regulator–who is operating relatively freely of political constraints imposed by fuel suppliers. Conversely, both opacity of the procurement process and political influence tend to raise input prices above levels observed by plants operating in a competitive market. Finally, divested plants are anticipated to favor less capital-intensive production methods than when they are compensated based on their capital stock.

1.4 Estimation Strategy

To estimate the impact of plant divestiture on coal procurement practices, one would ideally like to randomly assign treatment (divestiture) to observationally equivalent plants in close proximity. The control plants would continue operating under cost-of-service. With random assignment, these plants would serve as a clean counterfactual for the operations of the divested plants, allowing causal inference to be made. Forced divestitures triggered by state-level restructuring legislation has ensured that probability of treatment *within* state is uncorrelated with potential confounders. Complete divestiture of all generating assets guaranteed regulated utilities were not left operating the least desirable plants in their portfolio, for example. However, it is clear from Figure 1.1 that restructuring legislation was not randomly assigned *across* states.

With a panel of data on costs and plant characteristics, one could potentially account for the differences between treatment and control groups with a Differences-In-Differences estimator (DID, Ashenfelter (1978) and Ashenfelter and Card (1985)). This is the approach taken by Bushnell and Wolfram (2005), Davis and Wolfram (2012), and Chan, Fell, Lange, and Li (2012) when studying the effect of divestiture on plant efficiency. A DID framework with plant-level fixed effects assumes

Figure 1.2: *Estimated Shipping Costs per MMBTU of Coal*



Note: Estimated shipping costs are derived from a regression of delivered costs on a polynomial of coal characteristics, distance to the mine, and dummies for time, place of origin, and site of delivery. The relationship between estimated shipping cost and distance is then fit with a local polynomial expansion of shipping distance.

that once permanent, plant-specific determinants of cost have been removed, coal prices at control facilities track the counterfactual prices at treatment facilities. This assumption is problematic in settings where unobserved or endogenous time-varying determinants of the outcome variable differ between treatment and control groups. In the case of coal procurement, the combination of substantial shipping costs and wide geographic dispersion of plants between treatment and control groups suggests that a straightforward DID estimation would be inappropriate.

For example, Figure 1.2 shows the estimated relationship between plant distance from mine and shipping costs during three of the past twenty years (1997 is year before divestitures begin).[19] Fluctuations in the price of oil, and their subsequent effect on freight rates will disproportionately influence prices at facilities farther from their supplier because shipping rates are tightly connected to oil prices. However, simply controlling for distance from the mine is unsatisfactory—part of the goal of this paper is to test whether firms differentially respond to cost shocks. If a divested firm

[19]While shipping is charged per ton of coal, not per unit of heat, all coal data in this paper is denominated in Millions of British Thermal Units (MMBTU). This is because heat energy is fundamentally what is being converted to electricity, and the heat content per ton of coal varies.

is more likely to change their supplier in response to cost spikes, the savings from the change itself will be lost when limiting to estimation conditional upon distance.

Another possible approach would be to use the synthetic control group approach of Abadie and Gardeazabal (2003) and Abadie, Diamond, and Hainmueller (2010), who match on pre-treatment outcome variables. Again, the potential confounders in this setting render such an approach problematic. This is because in the pre-treatment years, a facility in Chicago may be matched with a facility in Atlanta that receives its coal from West Virginia, roughly equal distance between the two. The plant in Atlanta, however, is a poor counterfactual for the relative prices of coal ranks in Chicago, which is much closer to the Powder River Basin in Wyoming. They may have identical prices at baseline, but face different choice sets unrelated to treatment status.

Instead, I compare facilities in close proximity that burned the same rank of coal in 1997, before divestitures began.[20] More formally, suppose we have N plants indexed $i \in \{1, ..., N\}$ so that plants $i \in \{1, ..., N_0\}$, $N_0 < N$ are never divested, but those with $i \in \{N_0 + 1, ..., N\}$ eventually are. There are T time periods indexed $t \in \{1, ..., T\}$, and T_0 pre-treatment time periods with $1 < T_0 < T$. Using the 'Potential Outcomes' framework of Fisher (1935), Roy (1951), and Rubin (1974), let $Y_{it}(0)$ denote the price of coal per MMBTU paid by a non-divested facility i in period t. Similarly, let $Y_{it}(1)$ denote a facility that has been divested. Suppose fuel costs at non-divested facilities are

$$Y_{it}(0) = \gamma_i + \delta_t + c_t(X_i, 0) + \nu_{it}$$

where $c_t(X_i, 0)$ represents a time-varying procurement cost function that depends on facility i's location X_i (a richer set of pre-treatment covariates is possible), and regulatory status. Suppose that divestiture induces procurement cost $c_t(X_i, 1)$, but that time invariant costs γ_i are unaffected by regulatory status (an example would be "last mile" costs that are idiosyncratic to the plant). Then coal prices at divested facilities can be written as

$$\begin{aligned} Y_{it}(1) &= Y_{it}(0) + [c_t(X_i, 1) - c_t(X_i, 0)] \\ &= Y_{it}(0) + \tau_t(X_i) \end{aligned}$$

[20]The variance in heat, sulfur, and ash content across rank is much greater than within rank, so switching across ranks requires more costly adjustments than the tuning needed to switch suppliers within rank. The procurement options available to two plants in close proximity are likely to overlap when they burn the same rank of coal.

where $\tau_t(X_i)$ represents the relative procurement cost between being divested and regulated at location X_i in period t. The observed fuel price at plant i in period t is therefore

$$Y_{it} = Y_{it}(0) + \tau_t(X_i)D_{it}$$

where

$$D_{it} = \begin{cases} 1 & \text{if } i > N_0 \text{and } t > T_0 \\ 0 & \text{otherwise.} \end{cases}$$

The difficulty in estimation is that only control facilities in close proximity to X_i are suitable to serve as counterfactuals for the price $Y_{it}(0)$, and only after permanent facility-specific differences and common transitory shocks have been taken into account. The estimation strategy employed is similar to the conditional DID estimator of Heckman, Ichimura, Smith, and Todd (1998), but matches on geographic proximity and binary baseline characteristics (rank of coal burned), rather than the propensity score.

As in the matching literature (Abadie and Imbens (2006); Dehejia and Wahba (1999); Heckman, Ichimura, and Todd (1997)), let $1\{\}$ denote an indicator function that evaluates to one if the statement in braces is true, and let $D_i \equiv max\{D_{it}\}$ denote treatment group, and $l_m(i)$ be the index of facilities with $D_l \neq D_i$ and

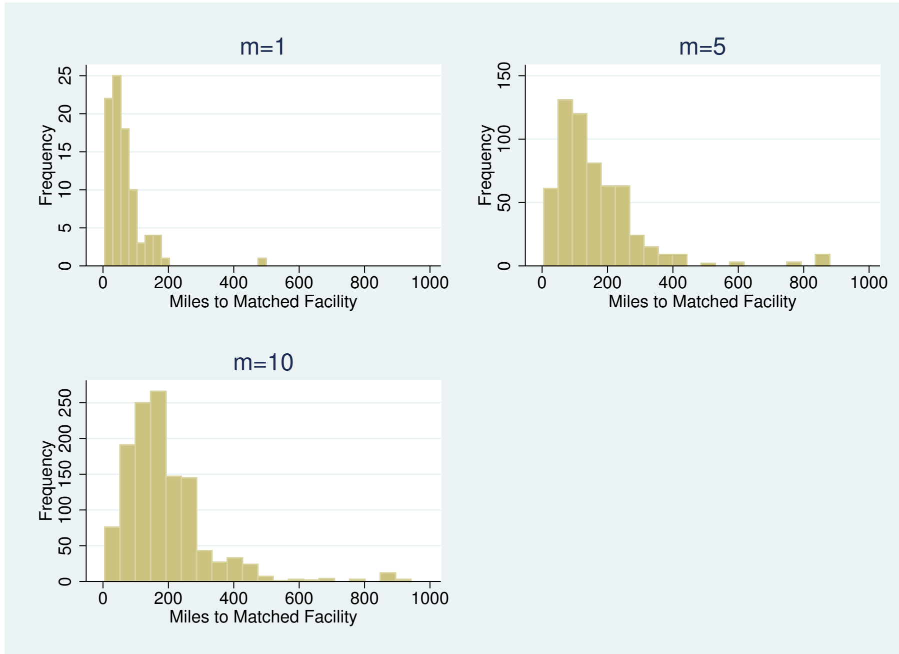
$$\sum_{j|D_j \neq D_i} 1\left\{\|X_j - X_i\| \leqslant \|X_l - X_i\|\right\} = m \tag{1.3}$$

Equation (1.3) identifies the m closest facilities of the opposite treatment group according to the norm metric $\| \centerdot \|$. I match exactly on the most common rank of coal (bituminous, sub-bituminous, or other) burned at baseline, then based on geographic proximity. An alternative approach is to match all facilities j with a caliper on distance, $\|X_j - X_i\| < d$, rather than based on a fixed number of matches. Results will be shown to be robust to the choice of matching metric. With a (possibly unbalanced) panel, it is possible to estimate $\tau_t(X_i)$ with a DID estimator applied to facilities i and the m facilities whose distance from X_i satisfies (1.3):

$$Y_{it} = \gamma_i + \delta_t + \tau_t(X_i)D_{it} + \varepsilon_{it}$$

The average treatment effect on the treated, $\tau = E[\tau_t(X_i)|D = 1]$ can be estimated by taking

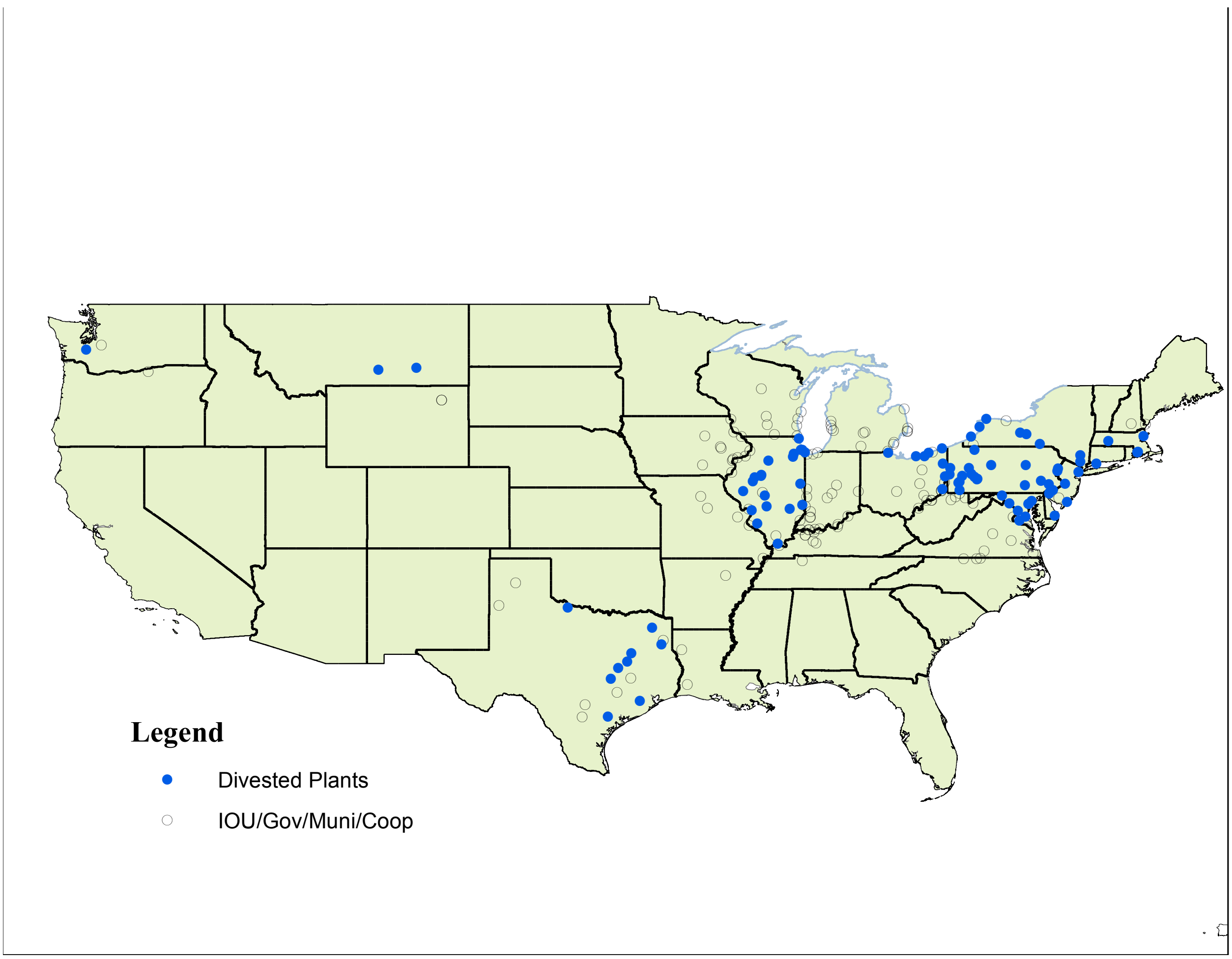
Figure 1.3: *Distance Between Divested and Matched Facilities*



the average over the divested facilities of the derived $\hat{\tau}_t(X_i)$, or more efficiently, by pooling the data of the divested facilities and their nearest neighbors in a single fixed-effects DID estimation (Angrist and Krueger (2000)), that weighs each matched control facility by the inverse of the number of matches to facility i in period t, then clusters standard errors at the facility level.

Figure 1.3 shows the distribution of distance between divested and matched facilities under three potential thresholds. All facilities are matched exactly on the predominant rank of coal burned at the facility in 1997, the final common pre-divestiture year. All facilities but one have at least a single match within 200 miles. All results based on matching the m closest non-divested facilities constrain the search radius to 200 miles–beyond this point diminishes the quality of the counterfactual without much gain in terms of broadening the sample. Estimates based on various search radii show that the results are not particularly sensitive to this choice of cut-off. Constraining the sample to these matches yields the set of facilities shown in Figure 1.4. It is clear that this estimation strategy is not well suited to estimating an average treatment effect for all U.S. plants, as the facilities in South-East, Upper Mid-West, and South-West are all hundreds of miles from the nearest divested facility. It is therefore not possible to estimate a credible counterfactual of how these non-divested plants would have operated if they had been subject to divestiture with

Figure 1.4: *Divested and Control Coal-Fired Plants within 200 miles*



this framework.

1.5 Data

This study utilizes a detailed and comprehensive panel dataset I have constructed from a combination of publicly-available and restricted-access data on the operations of the U.S. electricity sector from 1990-2009. Data on fuel expenditures, generating unit configurations, plant operations and regulatory status are from the Department of Energy's Energy Information Administration (EIA), and the Federal Energy Regulatory Commission. Data on the mines from which coal is sourced is from the Mine Safety and Health Administration (MSHA), the U.S. Geological Survey (USGS), and the Bureau of Labor Statistics (BLS). Appendix A describes each of the constituent elements in greater detail. Instead, this section focuses on describing the data in the context of potential threats to the validity of the proposed estimation strategy.

Plant-Level Characteristics

Table 1.1 presents summary statistics of plant characteristics by treatment group.[21] Panel A includes all facilities that report coal receipts in 1997, the common baseline year before divestitures begin. While divested plants are a few years older, the only substantial difference between the two groups is the likelihood of being subject to an Incentive Regulation program, a common precursor to restructuring. Panel B weights the data from non-divested plants in proportion to the number of divested plants matched for $m = 10$, subject to the constraint that plants be within 200 miles. Matching removes two-thirds of the non-divested plants from the sample, but only one divested facility is without any matches meeting this criteria. The high degree of balance between the two groups is consistent with the history of power plant construction. Generating capacity is closely related to economic activity, which is spatially correlated. It therefore makes sense that areas that grew together in the middle of the 20^{th} century made similar decisions to expand their generation capacity. Again, the exception is exposure to Incentive Regulation, which is consistent with the relationship with eventual restructuring. The fact that divested plants were disproportionately

[21]The data series upon which this table is based is described in Appendix A.

Table 1.1: *Characteristics of Divested and Non-Divested Plants in 1997*

A. All Facilities

	Divested	Not Divested	Difference of Means
Capacity (MW)	799.79	797.48	2.32
	[671.86]	[730.74]	(82.63)
Annual Capacity	0.59	0.57	0.02
Factor	[0.19]	[0.18]	(0.02)
Plant Vintage	1961.99	1964.72	–2.73*
	[10.92]	[13.53]	(1.39)
% Scrubbers	0.25	0.32	–0.07
Installed	[0.44]	[0.47]	(0.05)
Incentive	0.44	0.15	0.29***
Regulation Util.	[0.50]	[0.36]	(0.06)
Facilities	88	309	397

B. Matched Facilities

	Divested	Not Divested	Difference of Means
Capacity (MW)	803.95	648.72	155.23
	[674.61]	[657.66]	(119.86)
Annual Capacity	0.59	0.55	0.04
Factor	[0.19]	[0.22]	(0.05)
Plant Vintage	1962.14	1962.91	–0.78
	[10.90]	[14.04]	(2.20)
% Scrubbers	0.25	0.26	–0.01
Installed	[0.44]	[0.44]	(0.08)
Incentive	0.45	0.07	0.38***
Regulation Util.	[0.50]	[0.25]	(0.06)
Facilities	87	101	188

Note: Non-Divested facilities in Panel B receive weight $1/m_j$ for each matched divested facility j. Matching criterion: $m = 10$ burning the same rank of coal in 1997, subject to the constraint that distance be less than 200 miles. Standard errors clustered by facility in parentheses. * p<0.1, ** p<0.05, *** p<0.01

already attempting to reduce costs suggest findings may be somewhat biased against subsequent cost reductions.

It is important to note that entry and attrition of coal-fired plants was rare during the sample period, and are unlikely to be sources of bias. Stringent environmental regulations on new boilers combined with high capital costs have made new coal plant construction largely uneconomical. In total, 96% of coal heat in 2009 was delivered to plants reporting in 1990 (slightly more after accounting for the non-reporting of permanent non-utilities prior to 2002). As a fraction of plants, 92% of plants reporting in 2009 also reported in 1990. For attrition, the combination of high entry costs with the high option value from operating during periods of peak demand justifies maintenance costs at most aging facilities. 94% of plants operating in 1990 continued to report fuel deliveries in 2009. The plants that closed tended to be small and rarely used–as a group they accounted for less than 2% of the heat delivered in 1990.

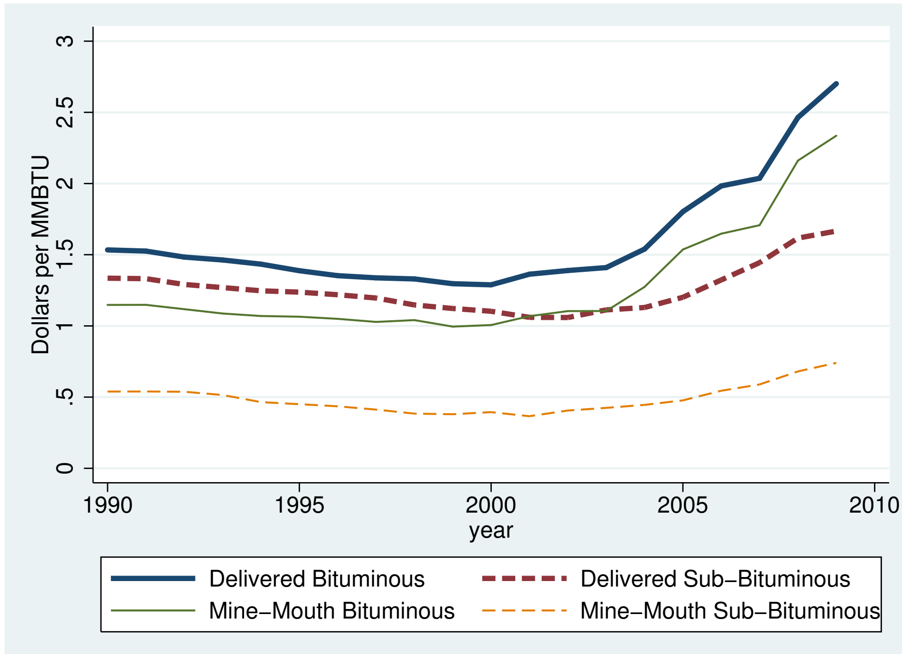
Data on The Cost and Quality of Coal

Figure 1.5 shows how nominal delivered and mine-mouth prices of bituminous and sub-bituminous coal have evolved over time. This figure again emphasizes the importance of shipping costs, as the price of bituminous coal is nearly 50% higher upon delivery than at the mine, and sub-bituminous prices more than double. This figure also shows a reason for the increasing popularity of sub-bituminous coal, as the average delivered price has fallen below the mine-mouth price for bituminous. While the delivered price depends on the spatial distribution of selected plants, the crossing in the early 2000's means that for plants that switched, sub-bituminous was cheaper on average than bituminous coal, even for plants located at a bituminous mine-mouth. After flat or declining prices through much of the nineties, the delivered price of coal has roughly doubled for bituminous and increased by about 50% for sub-bituminous coal over the last decade. Increases in mine-mouth prices only account for about half of the rise in sub-bituminous prices, the rest is due to increased shipping costs (both in terms of shipping rates and expanded delivery areas). Increases in bituminous prices since 2003 are largely due to increased mining costs and international demand.[22] All told, expenditures on coal for generating electricity averaged about $23B through most of the nineties, and has increased rapidly since 2002 to about $40B in 2009 (detailed figures are presented in Appendix A). Expenditures among divested facilities since reporting commenced in 2002 is about $8B per year on average.

Figure 1.6 breaks down average delivered coal prices by regulatory category. The vertical lines in the figure denote the year that divestitures began (1998), and the year that the EIA began collecting data from non-utility plants (2002). There is therefore a gap in reporting for any plant that was divested prior to 2002. It should be kept in mind that between these lines there are

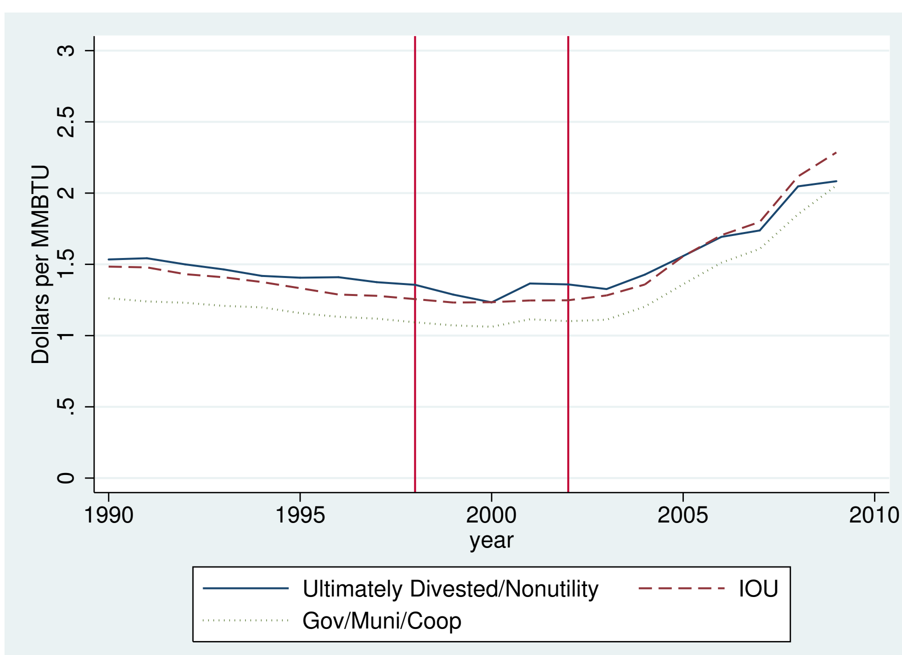
[22]Crippling weather events in Chinese and Australian coal fields in 2007 led to a spike in demand for U.S. bituminous coal, causing the price to rise nearly 50% (intra-year spikes were even higher).

Figure 1.5: *Price per MMBTU by Coal Type, 1990-2009*



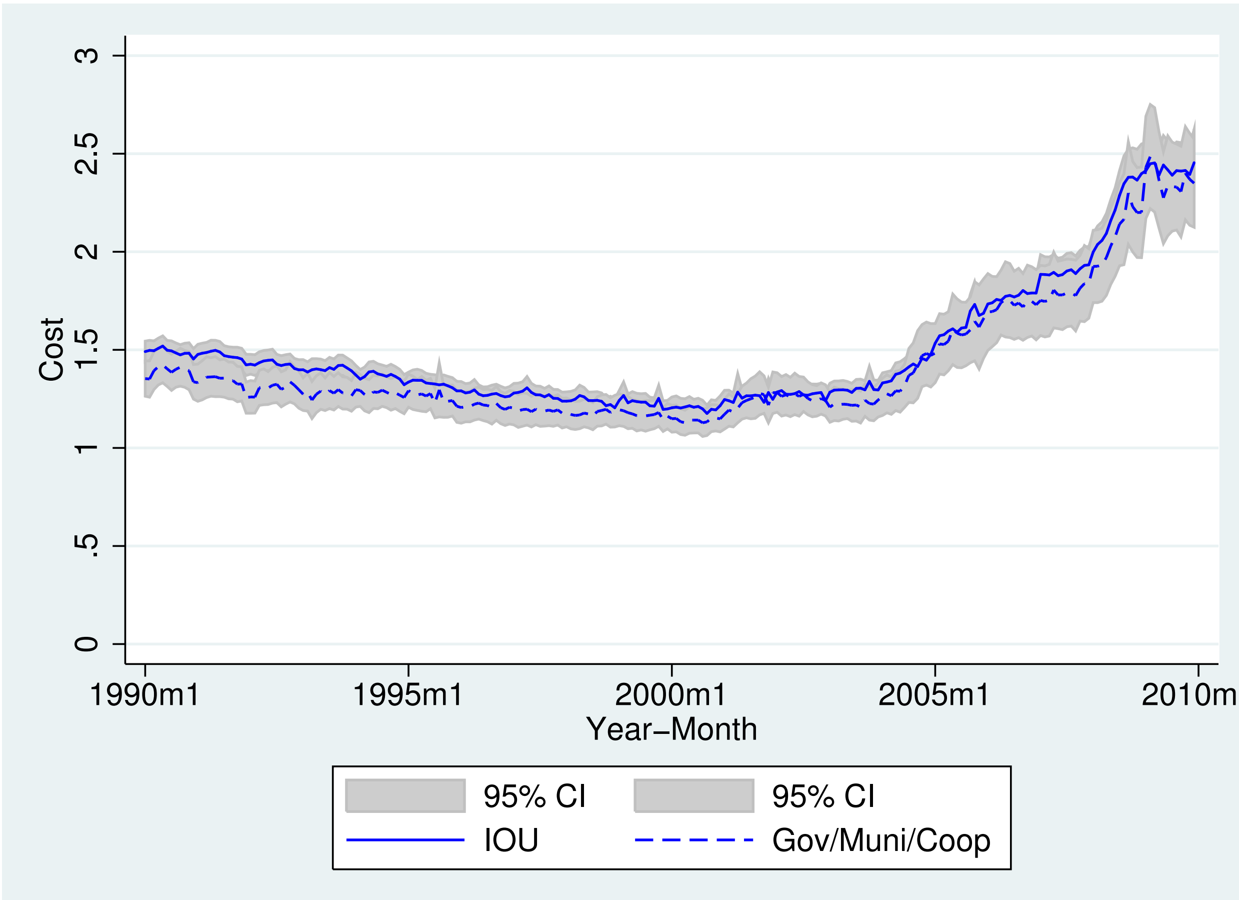
Note: Mine-mouth prices from EIA Annual Energy Review (2011), Table 7.9 and converted to heat units using average heat content by year and rank as reported in Forms EIA-423,923 and FERC 423.

Figure 1.6: *Coal Price per MMBTU by Divestiture Class, 1990-2009*



Note: Vertical lines denote the year in which divestitures begin (1998), and when reporting for non-utilities commences (2002). Source: Forms EIA-423,923 and FERC 423.

Figure 1.7: *Matching Estimates of Delivered Coal Price at IOU and Gov/Muni/Coop Plants within 100 miles, 1990-2009*



Note: Gov/Muni/Coop facilities receive weight $\frac{1}{m_j}$ for each matched divested facility j. Matching criteria: $m = 10$, burning the same rank of coal in 1997, subject to the constraint that distance be less than 200 miles. Confidence intervals based on standard errors clustered by facility.

compositional changes in the data.[23] Prior to 1998, the facilities that were ultimately divested operated as IOUs, and had somewhat higher prices than IOUs that did not face restructuring. Divested plants are at parity with their IOU counterparts shortly after reporting commences, and by the end of the sample period they have reduced the average cost paid for coal to the levels achieved by Gov/Muni/Coop plants.

Although Gov/Muni/Coop plants do not face any changes in regulatory oversight during this period of time, it is not obvious that the incentives facing operators of these plants would parallel those of IOUs, a necessary condition to use these facilities to form a counterfactual for

[23]See Appendix A for a detailed discussion.

divested plants. This is a testable assumption, and Figure 1.6 provides informal evidence of its validity: IOU and Gov/Muni/Coop price paths are parallel throughout the period of study. Figure 1.7 tests this hypothesis more formally using the matching methodology developed in Section 1.4 with $m = 10$. IOU plants not subject to divestiture are matched to Gov/Muni/Coop facilities that burned a common rank of coal in 1997, and are within 200 miles of the matched facility. Since some facilities are not within 200 miles of 10 members of the opposite group, matched observations are weighted by $\frac{1}{m_j}$, the number of matches for facility j within 200 miles. The matched data is then pooled, and regressed against a set of group-month dummies, with 95% confidence intervals formed by clustering standard errors at the facility level. Once this re-weighting is performed, the difference between the two groups is statistically significant for one month over twenty years, and they follow nearly identical paths aside from a brief convergence in 2002. This suggests that Gov/Muni/Coop plants nearby divested facilities perform equally well as IOU facilities to estimate the counterfactual prices that would have prevailed in the absence of divestiture.

Table 1.2: *Characteristics of Coal Deliveries to Divested and Non-Divested Plants in 1997*

A. All Facilities

	Divested	Not Divested	Difference of Means
Millions MMBTU	44.76	44.18	0.58
Delivered	[42.78]	[43.01]	(5.16)
Price($/MMBTU)	1.42	1.20	0.21***
	[0.37]	[0.37]	(0.04)
% Spot Market	0.24	0.27	–0.03
	[0.29]	[0.32]	(0.04)
Yrs to Contract	5.37	7.95	–2.58***
Expiry	[6.19]	[7.21]	(0.88)
% Sourced	0.41	0.30	0.12**
In-State	[0.46]	[0.44]	(0.05)
% Bituminous	0.76	0.62	0.13**
	[0.42]	[0.46]	(0.05)
Sulfur Content	1.19	1.02	0.17*
(lbs/mmbtu)	[0.72]	[0.81]	(0.09)
Ash Content	8.67	8.03	0.64
(lbs/mmbtu)	[4.83]	[4.15]	(0.56)
Mine Distance	318.10	364.92	–46.82
(mi.)	[330.64]	[312.52]	(39.38)
Facilities	88	309	397

B. Matched Facilities

	Divested	Not Divested	Difference of Means
Millions MMBTU	44.93	37.36	7.57
Delivered	[43.00]	[37.48]	(7.19)
Price($/MMBTU)	1.42	1.30	0.12
	[0.37]	[0.34]	(0.08)
% Spot Market	0.23	0.27	–0.04
	[0.28]	[0.36]	(0.06)
Yrs to Contract	5.42	7.42	–2.00
Expiry	[6.23]	[7.92]	(1.28)
% Sourced	0.41	0.40	0.01
In-State	[0.46]	[0.45]	(0.08)
% Bituminous	0.76	0.76	–0.00
	[0.42]	[0.42]	(0.07)
Sulfur Content	1.19	1.34	–0.16
(lbs/mmbtu)	[0.73]	[0.87]	(0.14)
Ash Content	8.56	9.45	–0.89
(lbs/mmbtu)	[4.75]	[7.74]	(1.38)
Mine Distance	321.01	264.58	56.43
(mi.)	[331.42]	[299.16]	(47.52)
Facilities	87	101	188

Note: Non-Divested facilities in Panel B receive weight $1/m_j$ for each matched divested facility j. Matching criterion: $m = 10$ burning the same rank of coal in 1997, subject to the constraint that distance be less than 200 miles. Standard errors clustered by facility in parentheses. * p<0.1, ** p<0.05, *** p<0.01

Table 1.2 presents summary statistics on the characteristics of coal deliveries reported to FERC/EIA in 1997, the final year before divestitures began. As detailed in Joskow (1985, 1987, 1988), the market for coal is largely conducted through long-term bilateral contracts, with supplemental demand procured on the "spot market," which are short-term bilateral contracts in practice.[24]

At baseline there are substantial differences in the characteristics of coal delivered, though quantities are similar. Divested facilities pay substantially more for coal, both through contracts and on the spot market. They buy 12% more of their coal from within their home state, and are 13 percentage points more likely to be burning bituminous coal. Differences in sulfur content stem from the bias toward bituminous coal among divested facilities. Divested facilities tended to have about two and a half fewer years remaining on their coal purchasing contracts in 1997.

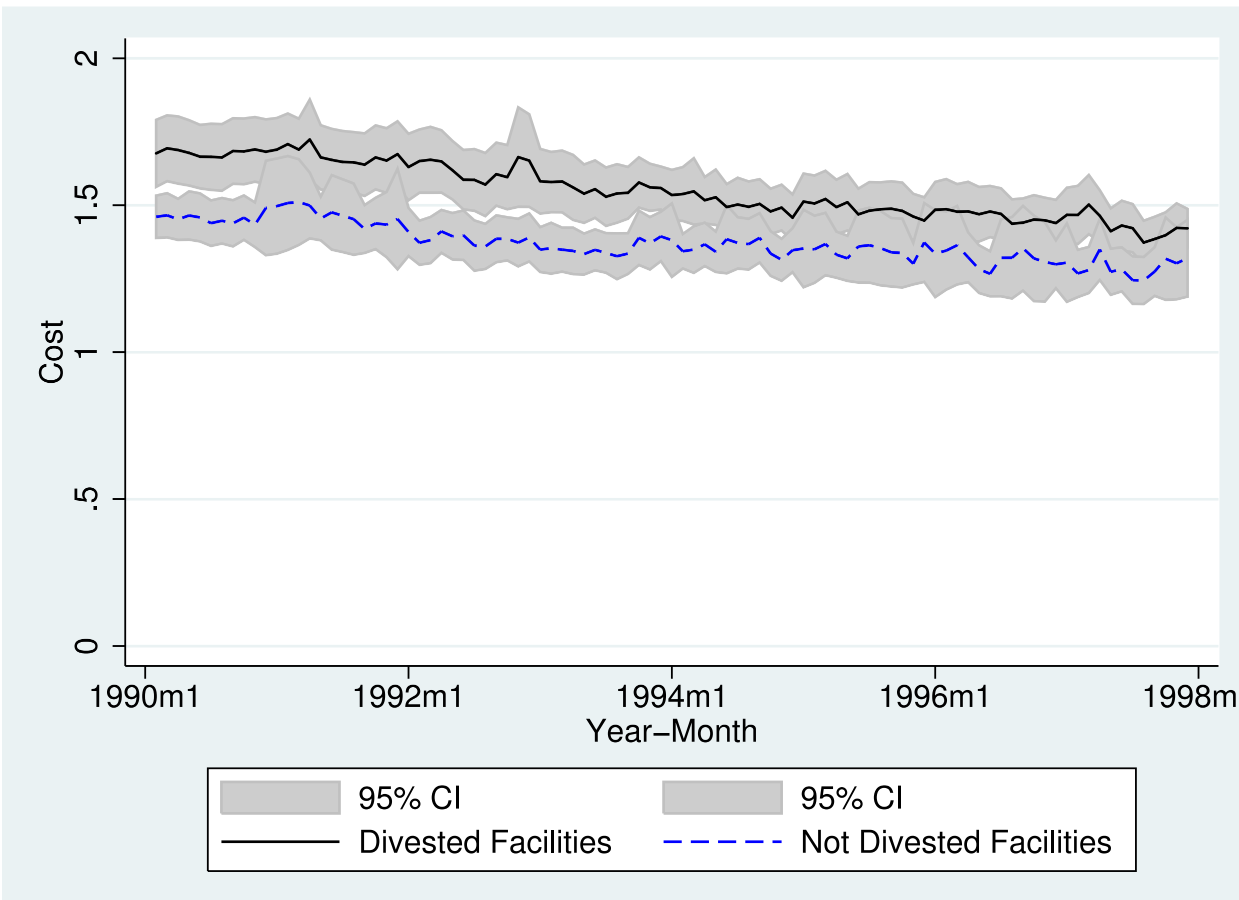
Many of the differences in the characteristics of coal purchases between divested and non-divested facilities are due to geographical dispersion, and are eliminated through matching. In fact, there are no statistically significant differences between coal delivered to divested plants and their matched counterparts.

Since the estimation strategy relies on comparing changes over time, it is also important to ensure that pre-existing trends are not responsible for the subsequent differences between treatment and control units. This does not appear to be the case using the complete, unweighted sample in Figure 1.6. Figure 1.8 examines the common pre-treatment period employing the methodology described above to compare non-divested IOU and Gov/Muni/Coop in Figure 1.7. It provides encouraging evidence that both treatment and control groups were following parallel paths throughout the '90s.[25] It appears that the 12 cent premium paid in 1997 by IOU facilities that would later be divested was a relatively constant feature of coal deliveries. It would be difficult to attribute the decline in prices paid by divested facilities in subsequent periods to mean-reversion, as there is no evidence that prices were moving in different directions before divestiture.

[24]These contracts typically take the form of "base plus escalation": initial prices are set to reflect current market conditions, and the price subsequently rises or falls based on a producer price index for coal production.

[25]If one squints, there might be a slight narrowing of the gap around 1993, perhaps due to the introduction of incentive regulation programs.

Figure 1.8: *Pre-Trend Test: Matching Estimates of Delivered Coal Price, 1990-1997*



Note: Non-Divested facilities receive weight $\frac{1}{m_j}$ for each matched divested facility j. Matching criteria: $m = 10$, burning the same rank of coal in 1997, subject to the constraint that distance be less than 200 miles. Confidence intervals based on standard errors clustered by facility.

Unit-Level Characteristics

Although coal deliveries are reported at the facility level, the decision to switch the rank of coal burned or install a scrubber is unit-specific (a coal-fired "unit" typically consists of a boiler connected to a generator, cooling and pollution abatement equipment). On average, there are two to three coal-fired units operating per facility.

Table 1.3 presents summary statistics on coal-fired unit characteristics, both nation-wide and in the matched sample. The number of facilities here and those in the plant-level analysis are slightly different due to reporting requirements at the unit-level. In addition, the matching criteria at the unit-level also includes the presence of a scrubber. This is important when estimating the differential probability of adding a scrubber after divestiture. This additional matching requirement eliminates a handful of divested facilities, and about 25% of non-divested facilities. As with the plant-level data, matching removes any statistically-significant differences between divested and non-divested units.

1.6 Results

This section evaluates the conditions under which divestiture led to a change in behavior by power plant operators, and relates these results to the hypotheses of theories of regulatory inefficiency. I begin with coal prices, and show the robustness of the estimation strategy to various assumptions and specifications. I then contrast the results for coal with those of natural gas as evidence of the importance of asymmetric information in distorting procurement decisions under regulation. I then look at sulfur regulation compliance decisions in the context of capital-bias hypotheses, and show that the disproportionate switch to low-sulfur coal among divested plants does not explain much of the observed drop in relative price. Finally, I constrain my analysis to plants that were initially burning in-state coal, and relate their change in procurement behavior to theories of regulatory capture by politically-active coal mines.

Table 1.3: *Characteristics of Divested and Non-Divested Generating Units in 1997*

A. All Units	Divested	Not Divested	Difference of Means
Boiler Vintage	1962.97	1965.25	–2.28***
	[10.65]	[12.43]	(0.84)
Connected	328.53	290.81	37.73*
Nameplate (MW)	[265.07]	[268.24]	(20.27)
Capacity Factor	0.77	0.79	–0.02
	[0.22]	[0.19]	(0.02)
Bituminous	0.80	0.79	0.01
	[0.40]	[0.41]	(0.03)
Potential Sulfur	11.43	8.61	2.82***
Emissions (1000 tons/yr)	[14.26]	[13.55]	(1.08)
% Scrubbers	0.16	0.20	–0.04
	[0.37]	[0.40]	(0.03)
Facilities	88	310	398
Generating Units	215	849	1064

A. Matched Units	Divested	Not Divested	Difference of Means
Boiler Vintage	1962.41	1963.95	–1.54
	[10.24]	[11.88]	(1.35)
Connected	325.91	281.13	44.78
Nameplate (MW)	[268.49]	[275.55]	(33.25)
Capacity Factor	0.77	0.76	0.01
	[0.22]	[0.25]	(0.04)
Bituminous	0.84	0.84	–0.00
	[0.37]	[0.37]	(0.04)
Potential Sulfur	11.35	11.54	–0.19
Emissions (1000 tons/yr)	[14.69]	[18.30]	(1.98)
% Scrubbers	0.13	0.13	0.00
	[0.34]	[0.34]	(0.04)
Facilities	79	76	155
Generating Units	197	197	394

Note: Non-Divested facilities in Panel B are weighted based on the number of divested facilities matched for $m = 10$ burning the same rank of coal and common scrubber status in 1997, subject to the constraint that distance be less than 200 miles. Standard errors clustered by unit in parentheses. * p<0.1, ** p<0.05, *** p<0.01

Table 1.4: *Coal: Matched DID Estimates of Log(Price) and Divestiture*

	(1)	(2)	(3)	(4)	(5)	(6)
Post-Divest	–0.124***	–0.188***	–0.152*	–0.124***	–0.128***	–0.136**
	(0.044)	(0.058)	(0.077)	(0.045)	(0.046)	(0.064)
m Nearest Neighbors				10	5	1
Proximity Threshold (mi.)	200	100	50			
Year-Month FE	Yes	Yes	Yes	Yes	Yes	Yes
Facility FE	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.721	0.712	0.668	0.723	0.726	0.738
Facilities	230	146	69	198	166	121
Divested Facilities	87	74	39	87	87	87
Obs.	47024	28449	12682	37495	32958	23336

Note: Dependent variable is $Log(Price)$ of Coal per MMBTU, including shipping costs. Non-Divested facilities receive weight $\frac{1}{m\_j}$ for each matched divested facility j burning the same rank of coal in 1997, subject to the indicated matching criterion. Standard errors clustered by facility in parentheses.
* p<0.1, ** p<0.05, *** p<0.01

Deregulation and the Price of Coal

Table 1.4 shows the percent change in price associated with plant divestiture using the matched DID estimator. To evaluate the robustness of the estimates to matching criteria, the first three columns use a caliper on distance, while the last three vary the number of matches. One shortcoming of the distance caliper approach is that the number of divested facilities with *any* matches within the specified distance drops off as the criteria becomes more stringent. Thus the composition of divested plants changes between columns (1) and (3). This caveat aside, all matching specifications show large and statistically significant drops in the relative price paid for coal following divestiture. The results using a fixed number of matches rather than a distance threshold are stable and significant regardless of the number of matches included. Taken together, these estimates show a 12-13% drop in the price that divested facilities have paid for coal relative to nearby generation stations that were similar both on the characteristics of the facility, coal, and trends before divestiture occurred. When using levels rather than logs, this is about 25 cents per MMBTU of coal heat delivered. Based on the post-divestiture period average annual coal expenditure at divested facilities (about eight billion dollars per year), the treatment on the treated estimate amounts to one billion fewer dollars per year being spent on coal, holding quantities constant.

One can see the effect that the weighting scheme employed by the matched DID estimator has by comparing the results from Table 1.4 with those of Table 1.5, which uses a standard

Table 1.5: *Coal: Difference-in-Difference Estimates of Log(Price) and Divestiture*

A. All Facilities:

	(1)	(2)	(3)
Post-Divest	–0.051	–0.054	–0.131***
	(0.035)	(0.035)	(0.041)
Divest	0.145***		
Facilities	(0.030)		
Year-Month FE	Yes	Yes	Yes
Facility FE		Yes	Yes
Division-Year FE			Yes
Divest States Only			
R^2	0.252	0.772	0.803
Facilities	397	397	397
Divested Facilities	88	88	88
Obs.	86225	86225	86225

B. By Distance:

	(1)	(2)	(3)
Post-Divest	–0.055	–0.069*	–0.137**
	(0.036)	(0.040)	(0.055)
Proximity Threshold (mi.)	200	100	50
Year-Month FE	Yes	Yes	Yes
Facility FE	Yes	Yes	Yes
R^2	0.733	0.700	0.712
Facilities	333	221	123
Divested Facilities	88	78	47
Obs.	71569	47324	26483

Note: Dependent variable is *Log(Price)* of Coal per MMBTU, including shipping costs. Panel B contains all divested facilities, and any non-divested facilities within the specified distance of a divested plant. Standard errors clustered by facility in parentheses. * p<0.1, ** p<0.05, *** p<0.01

difference-in-difference estimator. Panel A is based on the full sample of coal plants in the United States. Consistent with the mean price trends in Figure 1.6, divested plants as a group buy coal that is about 14% more expensive pre-treatment. The first two specifications rely on the assumption that divested and non-divested facilities would have followed parallel paths in the absence of restructuring–there are no time-varying differences between the two groups. Under this assumption, divestiture is associated with a modest, but statistically insignificant drop in purchased coal price.

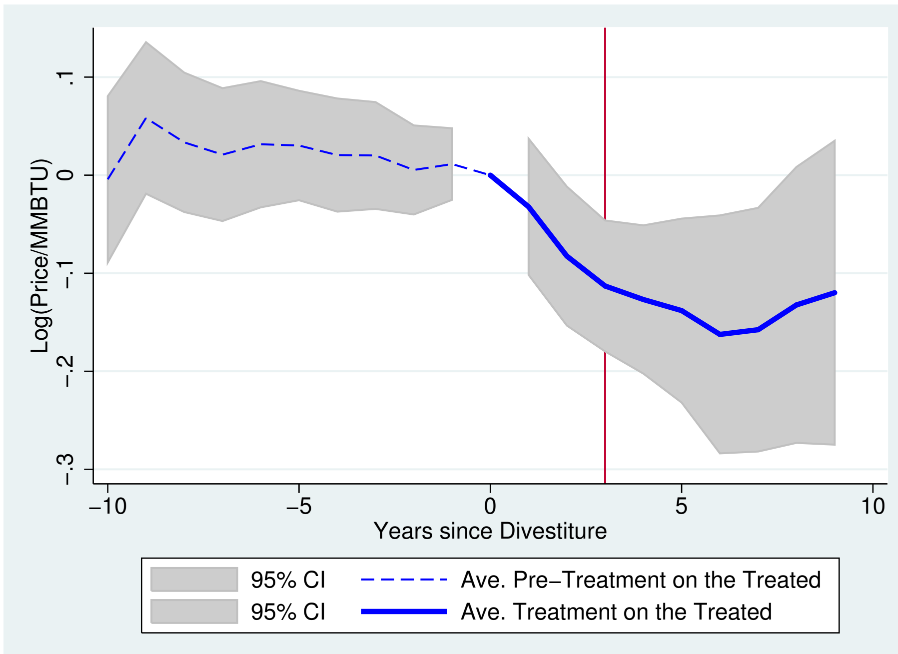
The third specification of Panel A relaxes the common-trend assumption by allowing the price of coal to vary by census division-year. As a result, the post-divestiture coefficient measures the percent change in coal prices at divested facilities compared to non-divested facilities within the same census division, which has a similar flavor to the approach proposed in Section 1.4. The drop in prices paid by divested coal plants is quite close to those of Table 1.4 using this specification.

Panel B of Table 1.5 is also based on a standard difference-in-difference estimator, but it limits the sample based on proximity to divested plants. This is an unweighted analog to columns (1)–(3) of Table 1.4, except that baseline rank of coal is not considered. Panel B shows that while estimates of the effect on coal prices remain negative, the magnitude is sensitive to the threshold distance for inclusion in the sample. At 100 miles, the coefficient is 7% and is only marginally statistically significant. However, the loss in precision from limiting the sample to closer facilities is more than offset by the substantial increase in the coefficient estimates for the other specifications. The weighting procedure used in Table 1.4 puts greater emphasis on non-divested plants in close proximity to multiple divested plants, and therefore stabilizes estimates somewhat in comparison to the unweighted approach.

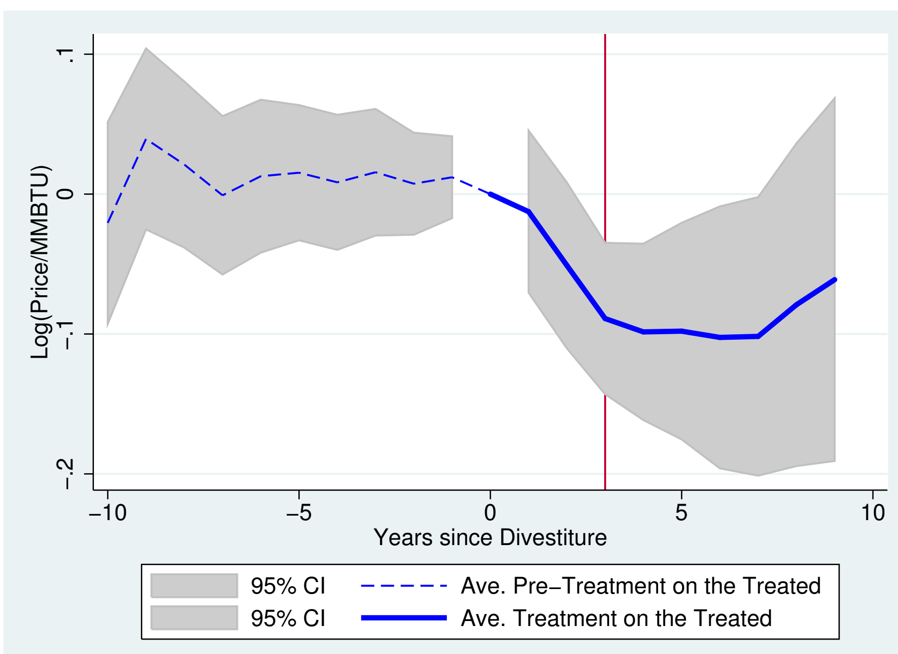
To evaluate the time path of the effect of divestiture, I interact an indicator variable for treatment facilities with a dummies indicating the time relative to year of divestiture in Figure 1.9. The omitted coefficient is the year prior to divestiture. Figure 1.9a is analogous to the average effect in column (2) of Table 1.4, and Figure 1.9b breaks out the results of column (4). Both panels show a flat relative price profile prior to divestiture that is close to, and statistically indistinguishable from zero. The corresponding figures at different thresholds share this characteristic (not shown). It appears that any changes that occurred after divestiture are not part of a continuation of a pre-existing trend. Again, one unfortunate characteristic of the data is plants divested prior to 2002

Figure 1.9: *Matching by Year from Divestiture: Log(Price)*

(a) *Distance < 100 Miles*



(b) *10 Nearest Neighbors*



drop out of the data immediately following sale. Since it took until 2002 for EIA to re-establish this reporting requirement under their authority, there is a gap in reporting for most facilities of the first couple years operating without utility commission oversight. The vertical line in year three represents the point where the majority of divested facilities resume reporting. If divestiture lead to an immediate change in operations, there would be a jump in the first year after sale. Instead, it appears the gains achieved by divested plants took a few years to settle in to a new, permanent level. This may be due to staggered expiration of contracts written before divestiture, but again it is difficult to draw conclusions based on the handful of plants for which data is available for the first two years after sale. The pattern of reductions for the other specifications are nearly indistinguishable from those in Figure1.9: a relatively stable period starting at year 3 at over 10% less than their regulated counterparts.

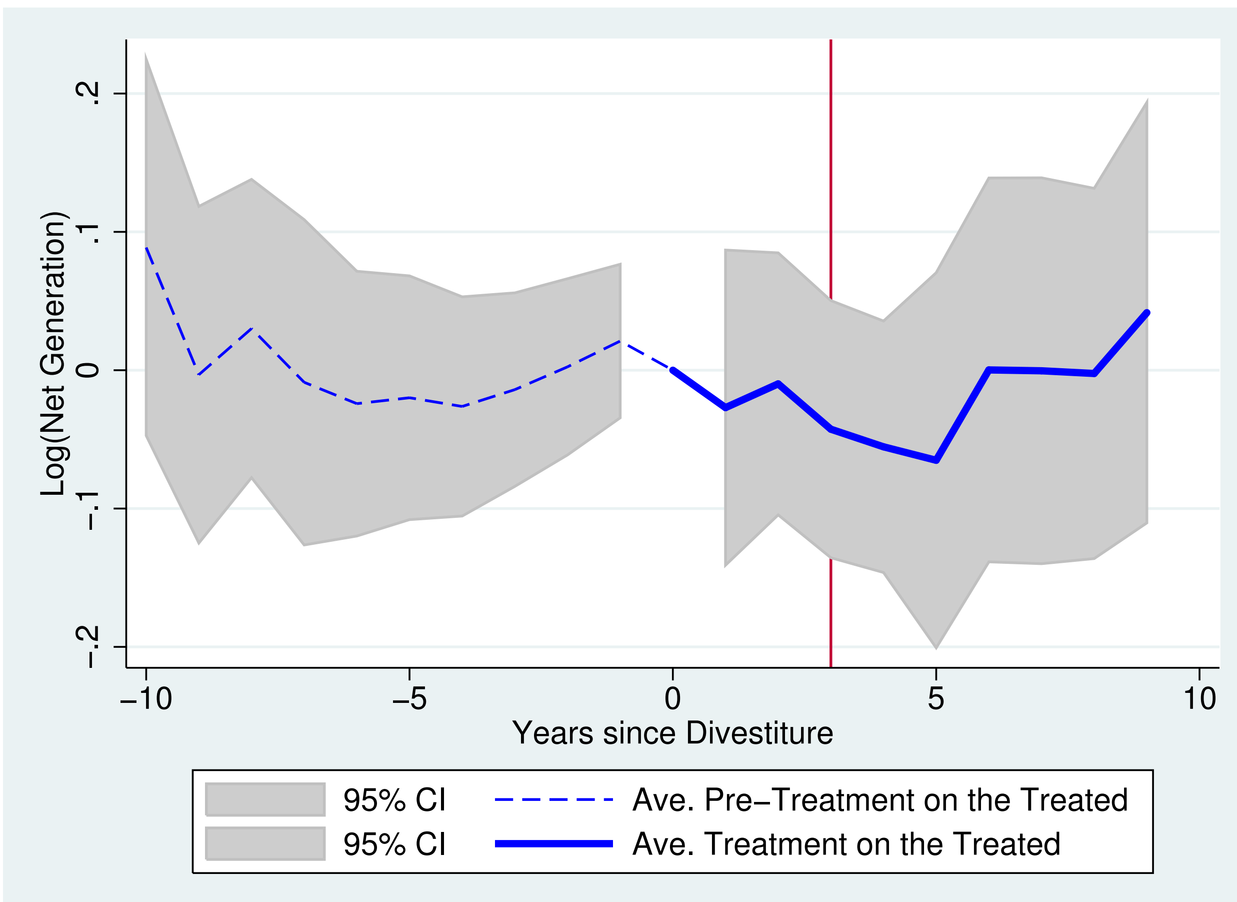
Before examining these results in the light of theories of regulatory inefficiency, it is important to rule out a rather simple hypothesis: that the relative change in price is due to changes in quantities demanded at coal-fired facilities. Figure 1.10 shows this is not the case: there has been no differential change in production between divested and non-divested plants. This may be explained by the fact that coal-fired units tend to be used for "baseload" generation–that is, they run at full capacity at all times except during maintenance periods.

Importance of Asymmetric Information: Comparison with Natural Gas

We have shown that coal burned for electricity is heterogeneous, and often sold via bilateral contracts. Furthermore, prices are location-specific due to high transportation costs. This makes it difficult for a regulator to know what purchasing opportunities are available to an operator, and whether the operator is exerting sufficient effort to keep costs low. By contrast, natural gas is a homogenous product (methane, mostly), traded on a transparent market.[26] Since it is delivered by a national network of pipelines that maintain pressure throughout the grid, transportation costs are essentially zero. This is evidenced by the fact that the price of gas at the Henry Hub in Louisiana rarely deviates from the price in New York. Since IOUs typically own the complete portfolio of generating plants, gas- and coal-fired facilities were subject to an identical change

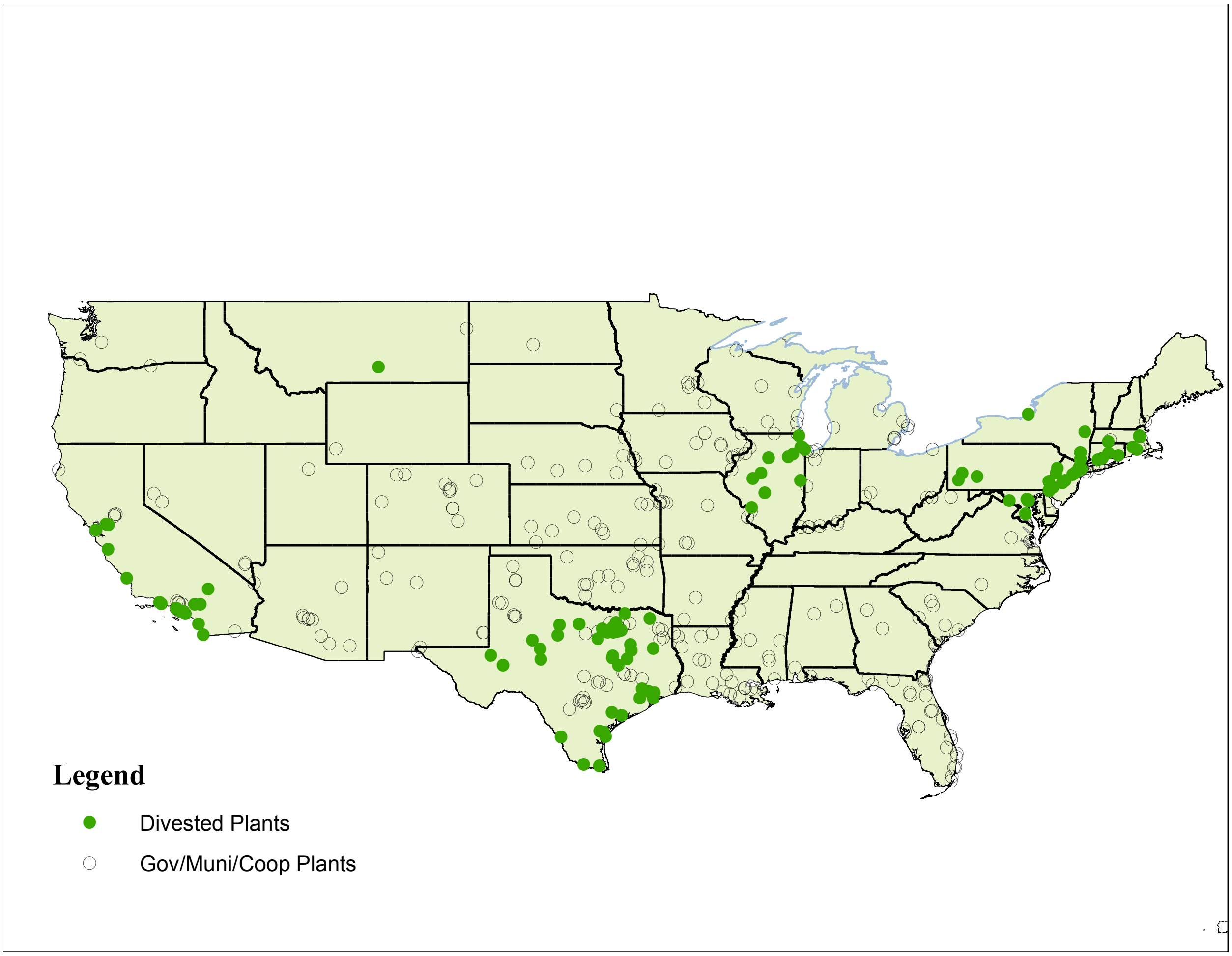
[26] A set of year-month dummies explains half of the variation in gas prices, but only one quarter of the variation in the delivered price of coal.

Figure 1.10: *Matching by Year from Divestiture: Log(Net Generation), 10 nearest neighbors*



Note: Non-Divested facilities receive weight $\frac{1}{m_j}$ for each matched divested facility j. Matching criteria: $m = 10$, burning the same rank of coal in 1997, subject to the constraint that distance be less than 200 miles. Confidence intervals based on standard errors clustered by facility.

Figure 1.11: *Divested and Control Gas-Fired Plants, 1990-1997*

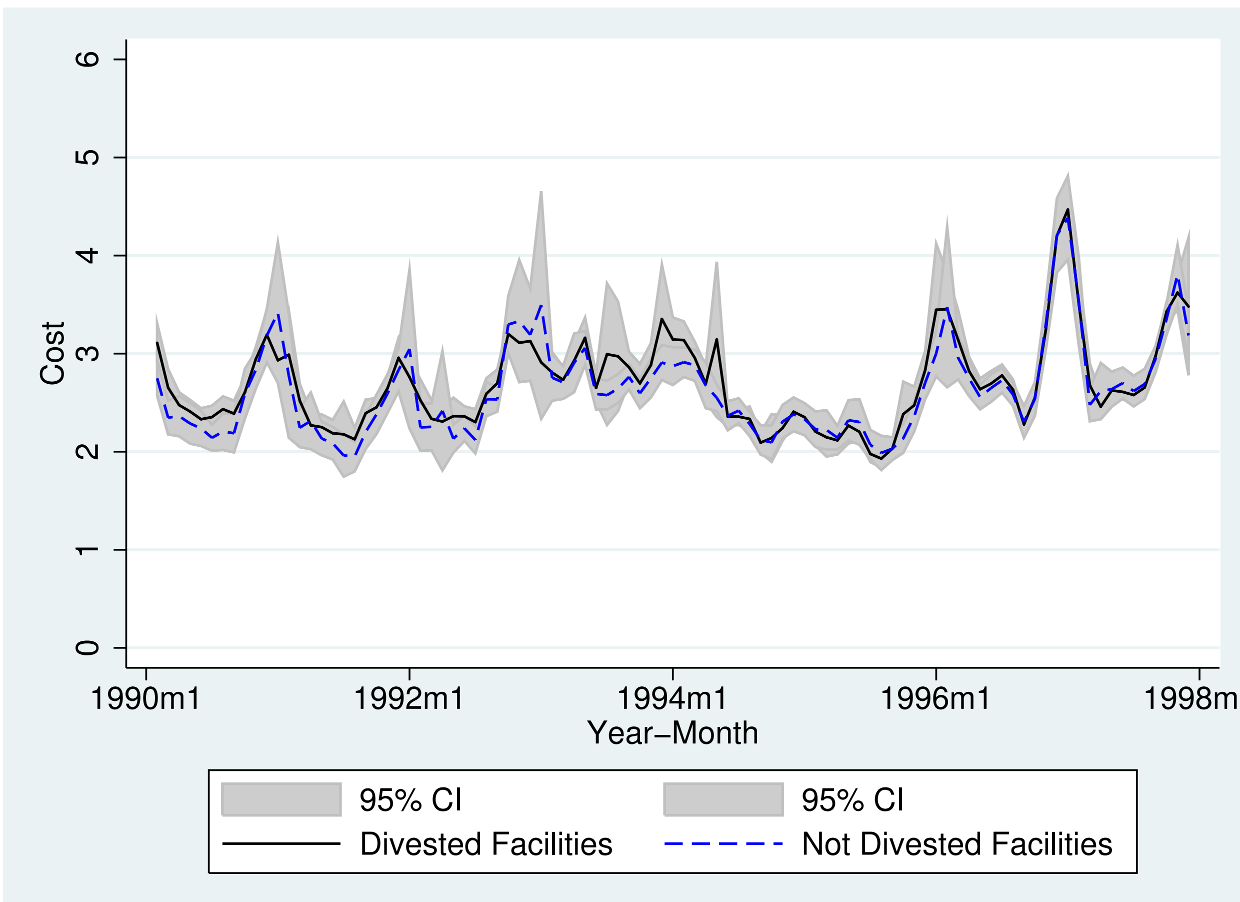


in regulatory structure. The importance of the interaction of information asymmetry and local capture can therefore be demonstrated by comparing the results for coal prices with those of natural gas.

Figure 1.11 shows the analogous map of divested gas-fired plants in the United States as of 1997. It is important to use this baseline because the recent drop in natural gas has lead to a boom in gas-fired generating capacity, much of which was never owned by an IOU, and therefore only began reporting costs in 2002. The key distinction between geographic distributions of gas- and coal-fired plants is that we now include the divestitures of California, which relies primarily on gas and hydro-powered generators.

Figure 1.12 shows the pre-treatment trends of prices paid by matched divested and non-divested plants. While gas prices are clearly more volatile than coal prices, divested and non-

Figure 1.12: *Pre-Trend Test: Matching Estimates of Delivered Gas Price, 1990-1997*



Note: Non-Divested facilities receive weight $\frac{1}{m_j}$ for each matched divested facility j. Matching criteria: $m = 10$, subject to the constraint that distance be less than 200 miles. Confidence intervals based on standard errors clustered by facility.

Table 1.6: *Gas: Matched DID Estimates of $Log(Price)$ and Divestiture*

	(1)	(2)	(3)	(4)	(5)	(6)
Post-Divest	0.012	0.027	0.010	0.012	0.005	0.038
	(0.026)	(0.029)	(0.036)	(0.027)	(0.027)	(0.038)
m Nearest Neighbors				10	5	1
Proximity Threshold (mi.)	200	100	50			
Year-Month FE	Yes	Yes	Yes	Yes	Yes	Yes
Facility FE	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.853	0.852	0.861	0.855	0.857	0.854
Facilities	276	198	111	254	224	165
Divested Facilities	109	99	59	109	109	109
Obs.	46828	33465	17631	41089	36727	26510

Note: Dependent variable is $Log(Price)$ of Gas per MMBTU. Non-Divested facilities receive weight $\frac{1}{m_j}$ for each matched divested facility j subject to the indicated matching criterion. Standard errors clustered by facility in parentheses. * p<0.1, ** p<0.05, *** p<0.01

divested prices co-move; there is no indication of a pre-existing differential trend between the groups.

Table 1.6 shows that divestiture has had essentially zero effect on the price generators pay for gas. This is true regardless of the matching criteria, and is relatively precisely estimated. In the case of gas, regulation was not distorting input price. It is important to point out that regulated IOUs operating coal-fired plants also tend to own gas-fired plants in order to meet changes in demand throughout the day. Thus the exact same operators whose coal prices changed substantially following divestiture were apparently making their gas procurement decisions efficiently. This implies that differences in the markets for coal and gas play a critical role in determining the potential for cost reductions following divestiture. The defining characteristics that differentiate these markets is price transparency and the room for discretion allowed by commodity heterogeneity, suggesting the importance of asymmetric information in creating the conditions that yield distortions under regulation.

Sulfur Emissions Compliance Decisions

Title IV of the Clean Air Act Amendments of 1990 capped the total emissions of sulfur oxides (which contribute to acid rain) allowed from major sources (i.e. coal-fired power plants), and created a market so that plants with high abatement costs could buy allowances instead of install abatement equipment. The market began in 1996 for the largest plants, with the remainder of coal-fired plants following soon after. Aside from buying allowances, plant operators had two

Table 1.7: *Matching DID Estimates of Sulfur Compliance Strategy*

	(1) Scrubber	(2) Low Sulfur	(3) Uncontrolled
Post-Divest	–0.072***	0.100***	–0.032
	(0.024)	(0.031)	(0.038)
Divested Unit	0.014	0.010	–0.023
	(0.040)	(0.034)	(0.047)
m Nearest Neighbors	10	10	10
R^2	0.017	0.049	0.056
Units	384	384	384
Divested Units	197	197	197
Obs.	7145	7145	7145

Note: Sample includes all units without a scrubber and burning bituminous coal in 1997. Non-Divested units receive weight $\frac{1}{m_j}$ for each matched divested facility j within 200 miles. Matching criterion: $m = 10$. Standard errors clustered by unit in parentheses. * p<0.1, ** p<0.05, *** p<0.01

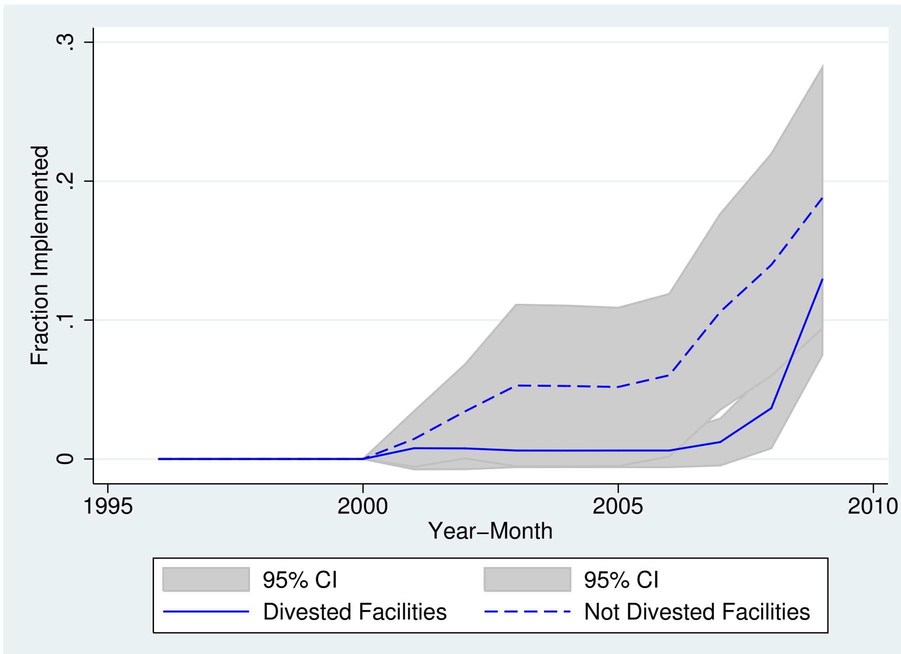
main options to comply with the new regulations: buy a flue-gas desulfurization system (called a "scrubber"), or switch to burning low-sulfur coal, typically from the Powder River Basin (PRB) in Wyoming. The Averch-Johnson hypothesis predicts that regulated plants will prefer to install capital-intensive scrubbers, which will add to their rate base.

Since scrubber installation is a permanent, binary outcome, it does not make sense to employ the matched DID approach described above. The behavior of managers that already have a scrubber installed is also uninteresting. I therefore perform a straightforward matching of divested and non-divested facilities that burned a common rank of coal, but did not have scrubbers installed in 1997. In recent work, Fowlie (2010) finds evidence consistent with the Averch-Johnson hypothesis in the context of compliance decisions for regional nitrogen oxide markets using a random-coefficients logit model. By contrast, the approach taken here is nonparametric. The benefit of this approach is that the results are free of the distributional assumptions that may cost more complex estimators some credibility. The main cost is that the structural approach identifies behavioral parameters that can be used to make out-of-sample predictions.

With this caveat in mind, Table 1.7 compares compliance decisions among generating units that were burning high-sulfur coal in 1997 without a scrubber installed. While divested units are clearly less likely to install scrubber, the seven percentage point difference masks the magnitude of how big this effect really is. Instead consider Figure 1.13a, which shows the differential rate of scrubber adoption. It is quite striking that only 3 of roughly 200 divested units install a scrubber

Figure 1.13: *Matching by Year from Divestiture: Sulfur Compliance Strategies , 10 nearest neighbors*

(a) $Pr(Add\ Scrubber)$



(b) $Pr(Switch\ Rank)$

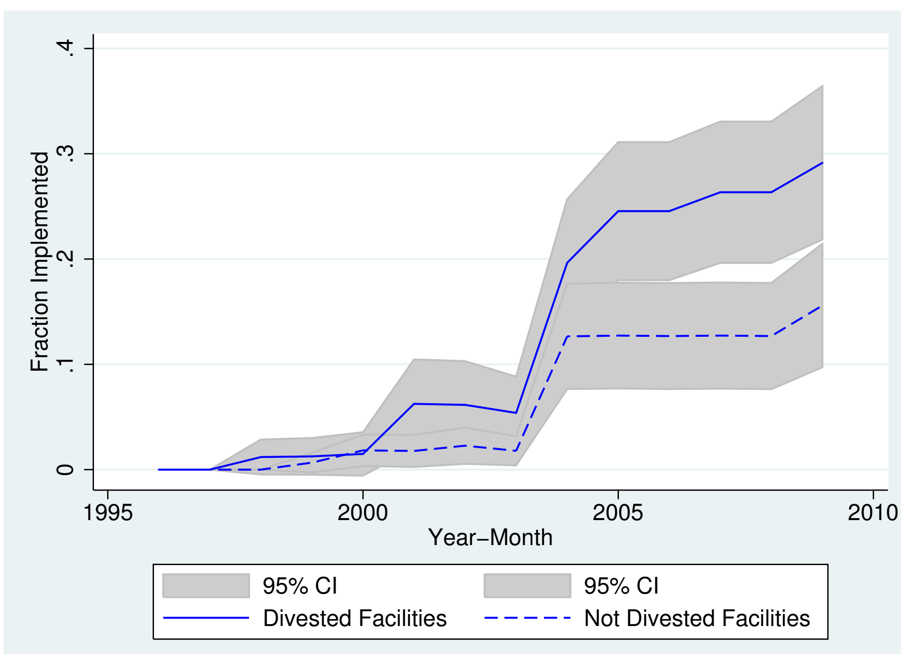


Table 1.8: *Matching DID Estimates of Log(Price) and Divestiture, by Coal Rank Switching and Import Status*

A. By Low-Sulfur Switching:	(1)	(2)	(3)	(4)	(5)	(6)
Post-Divest	–0.109**	–0.176***	–0.166*	–0.109**	–0.114**	–0.121*
	(0.050)	(0.067)	(0.091)	(0.051)	(0.052)	(0.068)
Post-Divest x	–0.053	–0.038	0.046	–0.052	–0.052	–0.053
Switching Plant	(0.048)	(0.057)	(0.092)	(0.048)	(0.049)	(0.049)
m Nearest Neighbors				10	5	1
Proximity Threshold (mi.)	200	100	50			
Year-Month FE	Yes	Yes	Yes	Yes	Yes	Yes
Facility FE	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.721	0.712	0.668	0.724	0.727	0.738
Facilities	230	146	69	198	166	121
Divested Facilities	87	74	39	87	87	87
Obs.	47024	28449	12682	37495	32958	23336

B. By Import Status in 1997:	(1)	(2)	(3)	(4)	(5)	(6)
Post-Divest	–0.157**	–0.244***	–0.250**	–0.157**	–0.161**	–0.169**
	(0.067)	(0.083)	(0.107)	(0.068)	(0.069)	(0.082)
Post-Divest x	0.066	0.115	0.210*	0.066	0.066	0.066
Initially In-State	(0.068)	(0.081)	(0.113)	(0.068)	(0.068)	(0.069)
m Nearest Neighbors				10	5	1
Proximity Threshold (mi.)	200	100	50			
Year-Month FE	Yes	Yes	Yes	Yes	Yes	Yes
Facility FE	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.722	0.715	0.679	0.724	0.727	0.739
Facilities	230	146	69	198	166	121
Divested Facilities	87	74	39	87	87	87
Obs.	47024	28449	12682	37495	32958	23336

Note: Dependent variable is $Log(Price)$ of Coal per MMBTU, including shipping costs. The treatment indicator in Panel A is interacted with dummies indicating whether the facility changes the predominant rank of coal burned after 1997. The treatment indicator in Panel B is interacted with dummies indicating whether the facility sourced its coal from within its home state in 1997. Main effects are absorbed in plant-level fixed effects. Non-Divested facilities receive weight $\frac{1}{m_j}$ for each matched divested facility j burning the same rank of coal in 1997, subject to the indicated matching criterion. Standard errors clustered by facility in parentheses. * p<0.1, ** p<0.05, *** p<0.01

up to six years after divestiture. It is only at the end of the sample that scrubber installation begins to pick up at divested units, so that they are about half as likely to install a scrubber by the end of the sample period. This result is relatively consistent across threshold specifications, with the difference being slightly larger when using a distance caliper rather than number of matches.

Instead, divested plants disproportionately chose to comply with sulfur emissions regulations by switching to sub-bituminous coal, as shown in Figure 1.13b. Since sub-bituminous coal has become relatively cheap in the past decade,[27] it may be that Averch-Johnson-type motives are the

[27]This may be surprising in light of the finding of Busse and Keohane (2007) that railroads exerted market power in

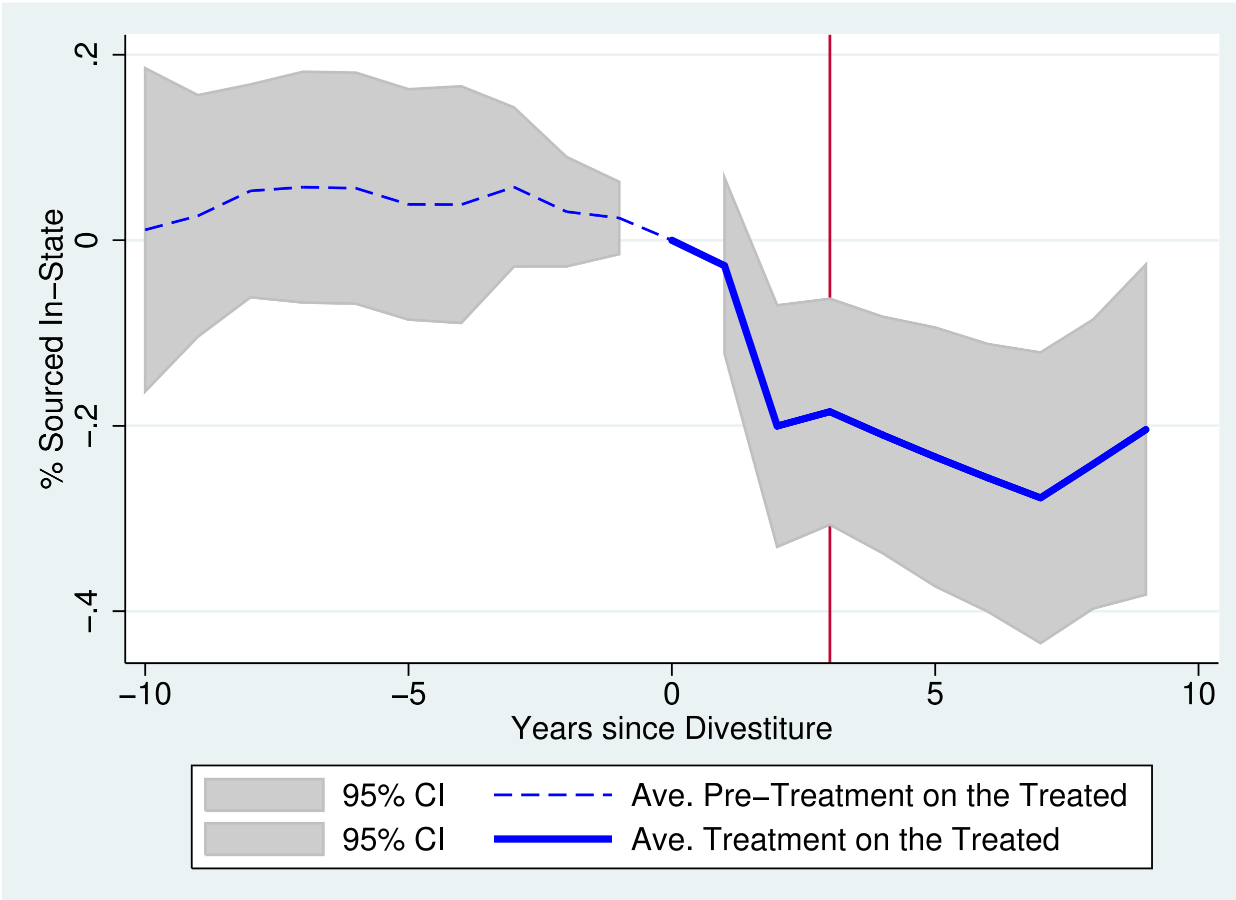
source of the observed drop in the price of coal among divested plants. One method of accounting for the role of fuel switching in cost savings estimates is to allow the treatment effect to differ between facilities that have switched the rank of coal they burn, and those who are still burning the same rank of coal as at baseline. Panel A of Table 1.8 reproduces the baseline estimates of Table 1.4, allowing for this heterogeneous treatment effect. The overall average price difference among plants that eventually switch is absorbed in the plant fixed-effects. It shows that facilities do in fact realize larger gains after having switched fuels–the total effect among switchers is obtained by adding the coefficients–though the difference is not statistically significant. This is not due to compositional differences between switchers and non-switchers: all but three facilities report at least one month of post-divestiture fuel purchases using the same rank of coal that was burned in the baseline year 1997. These post-divestiture purchases contribute to the non-switching estimate until the actual switch is made. Perhaps most important is the fact that around 90% of the gains seen overall are from facilities that have not switched to low-sulfur coal. While switching yields a larger drop, it accounts for a relatively small fraction of the overall treatment effect. This means that divested facilities were able to find and negotiate for cheaper coal, regardless of any motives to use low-capital methods to comply with sulfur emission regulations. The cost reductions found here are largely not an ancillary benefit of more fundamental motives to distort abatement techniques to more capital-intensive options among regulated utilities.

Regulatory Capture by Local Coal Producers

A distortion in the spirit of Stigler (1971) and Peltzman (1976) would exist if coal suppliers lobby the state regulator to force generators to buy from local coal mines. However, it is ambiguous *a priori* whether such a distortion would lead to larger or smaller gains in coal-producing states following divestiture. While there may be larger potential gains in these states, there is also likely to be greater resistance to keep them from being realized. Lile and Burtraw (1998), for example, document efforts undertaken by state legislatures to promote the purchase of local coal, ranging from subsidies to blatant mandates on the percent of coal that must come from within the state. While efforts to legislate such policies were voided by the courts under the

the face of greater demand for low-sulfur coal. However, increases in productivity over this period have more than offset demand shocks and markups. See Appendix A for a discussion of these trends.

Figure 1.14: *Matching by Year from Divestiture: Fraction of Coal Sourced In-State, 10 nearest neighbors*



Note: Sample is based on plants that sourced the majority of their coal from in-state in 1997. Non-Divested facilities receive weight $\frac{1}{m_j}$ for each matched divested facility j. Matching criteria: $m = 10$, burning the same rank of coal in 1997, subject to the constraint that distance be less than 200 miles. Confidence intervals based on standard errors clustered by facility.

Commerce Clause, it was still possible to make life for generators difficult via state oversight of environmental regulations. Panel B of Table 1.8 provides evidence suggesting that local coal may have been an impediment to fully realizing the potential gains from divestiture. It allows the effect of divestiture on $log(price)$ to vary between facilities that bought the majority of their coal from within their home state in 1997, and those who mostly imported. Although facilities that initially imported their coal consistently realized gains across specifications that are about 50% greater than plants that bought from within-state, the difference between the coefficients is not statistically significant. Furthermore, this can only be interpreted as suggestive evidence since geographic distance between these groups could also cause differences in realized cost reductions.

Table 1.9: *Matching DID Estimates of Percent of In-State Coal Among Plants Burning In-State Coal in 1997*

	(1)	(2)	(3)	(4)	(5)	(6)
Post-Divest	–0.093	–0.114	–0.111	–0.102	–0.107	–0.160***
	(0.058)	(0.073)	(0.072)	(0.065)	(0.065)	(0.055)
Post-Divest x	–0.374***	–0.351***	–0.342***	–0.374***	–0.373***	–0.377***
Switching Plant	(0.059)	(0.057)	(0.092)	(0.059)	(0.059)	(0.059)
m Nearest Neighbors				10	5	1
Proximity Threshold (mi.)	200	100	50			
Year-Month FE	Yes	Yes	Yes	Yes	Yes	Yes
Facility FE	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.687	0.667	0.689	0.682	0.679	0.718
Facilities	82	68	30	81	74	57
Divested Facilities	40	33	15	40	40	40
Obs.	17433	13745	5858	16802	14707	10820

Note: Dependent variable is % of Coal sourced from in-state. All plants in the sample sourced from in-state in 1997. Non-Divested facilities receive weight $\frac{1}{m_j}$ for each matched divested facility j burning the same rank of coal in 1997, subject to the indicated matching criterion. Standard errors clustered by facility in parentheses. * p<0.1, ** p<0.05, *** p<0.01

More definitive evidence of inefficient procurement practices under cost-of-service regulation in coal-producing states can be seen by examining changes in sourcing after divestiture. Recall that at baseline divested and non-divested plants are relatively balanced on the percent of coal sourced in-state. Table 1.9 limits the sample to divested and control plants that burned in-state coal in 1997. It measures the change in the fraction of coal sourced from in-state associated with divestiture. Since any plants that switch to sub-bituminous coal will mechanically increase their out-of-state purchases, it allows for heterogeneous effects between plants that switch, and those who do not. The goal here is to separate off switching motives from efforts to find lower cost producers that are not protected by state governments. If sourcing practices under regulation were efficient, one might see price drops as generators negotiated for larger fractions of the surplus, but there would be no reallocation of business to different mines. Table 1.9 shows this was not the case. Instead, divested facilities that initially sourced their coal in-state increased their out-of-state purchases, unconditional upon switching status.[28] While the biggest changes are among those who switch, there is also some evidence that plants in Pennsylvania, Ohio, and Illinois were able to find lower cost bituminous coal after divestiture (likely from Kentucky and West Virginia), although this effect is only statistically significant in one of the matching specifications.

[28]The coefficients are not minus one for switchers because this estimate is relative to the matched control facilities, who also switched ranks of coal, albeit at a lower rate.

Figure 1.14 breaks down the differential fraction of coal burned from in-state mines by year from divestiture. As with the price results, there is no evidence that the post-treatment coefficient is spuriously due to pre-existing trends. Instead, a flat pre-trend around zero is followed by a precipitous fall shortly after divestiture. In total, the relative fraction of coal sourced locally falls by about 25% during the post-divestiture period. While local coal lobbies may have prevented divested facilities from fully realizing the price reductions achieved in areas without coal deposits, they were not completely successful at mitigating the impact of divestiture on demand for their product.

Among the plants that switch to burning low-sulfur coal, it is not possible to distinguish between the importance of Averch-Johnson and regulatory capture with the current evidence: both theories predict that deregulated plants will be more likely to switch sub-bituminous coal, which is both lower in cost and capital-intensity. In fact, it is likely that the two forces are mutually-enforcing: eastern coal producers and regulated IOUs both stand to benefit from the installation of a scrubber. It is also not possible to identify the separate effects of asymmetric information and regulatory capture in coal-producing regions. However, the fact that there is no relative price drop for gas suggests that opacity in the market for coal creates the room needed for special interests to exert influence.[29]

1.7 Transfers versus Efficiency Gains

The large drop in price observed at divested coal-fired plants says little about the social welfare gains derived from restructuring. Even the substantial reallocation to out-of-state mines is consistent with minimal mining cost reductions. Suppose, for example, that out-of-state mines are only marginally more productive than in-state mines, the latter of which have been receiving regulatory rents. Prices fall and output shifts following divestiture, but to little effect in terms of the resources required to produce electricity.[30]

Fortunately the EIA data on coal deliveries includes information on the supplier and county

[29] For a theoretical treatment along these lines, see Coate and Morris (1995).

[30] The success of special interest groups that advocate for transfers with minimal welfare costs is predicted by Becker (1983, 1985).

of origin. I have linked these deliveries to characteristics of the mines from which the coal is derived. This includes quarterly data on the labor hours per ton (converted to hours per MMBTU to preserve consistency) from the Mine Safety and Health Administration, the associated wage bill from the Bureau of Labor Statistics, and data on the depth and thickness of coal seams from the U.S. Geological Survey. Seam depth measures how many feet underground must be dug before reaching the coal, and seam thickness measures how much coal per foot of horizontal digging can be recovered once the seam has been reached.

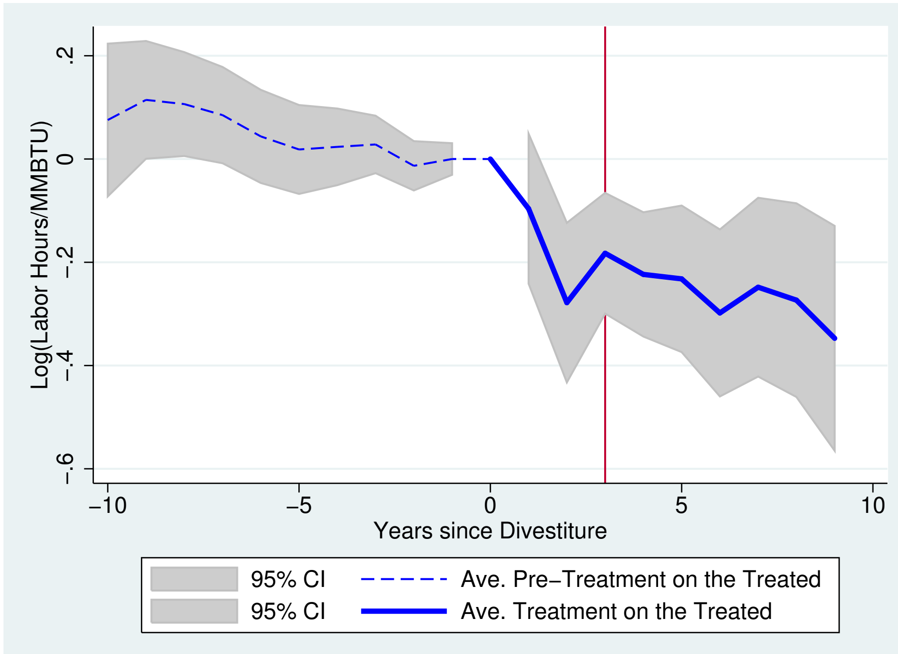
Figure 1.15 shows the effect of divestiture on the mining labor embodied in coal purchases. The difference between divested and matched plants prior to divestiture is relatively flat and insignificantly different from zero in both panels. The hours of labor required to mine coal then drops by about 25% for coal that is subsequently sold to divested plants, and this persists throughout the post-divestiture period. While hours drop, wages rise by about 5%–suggesting relative labor productivity gains at mines that sell to divested plants. Results are similar when considering the characteristics of the mines from which the coal is being sourced. Figure 1.16 shows that coal delivered to divested plants comes from seams that are about 30% thicker, and nearly 50% closer to the surface following divestiture. These results indicate that the shift in procurement following divestiture lead to substantial reductions in the cost of mining coal for electricity generation.

1.8 Conclusion

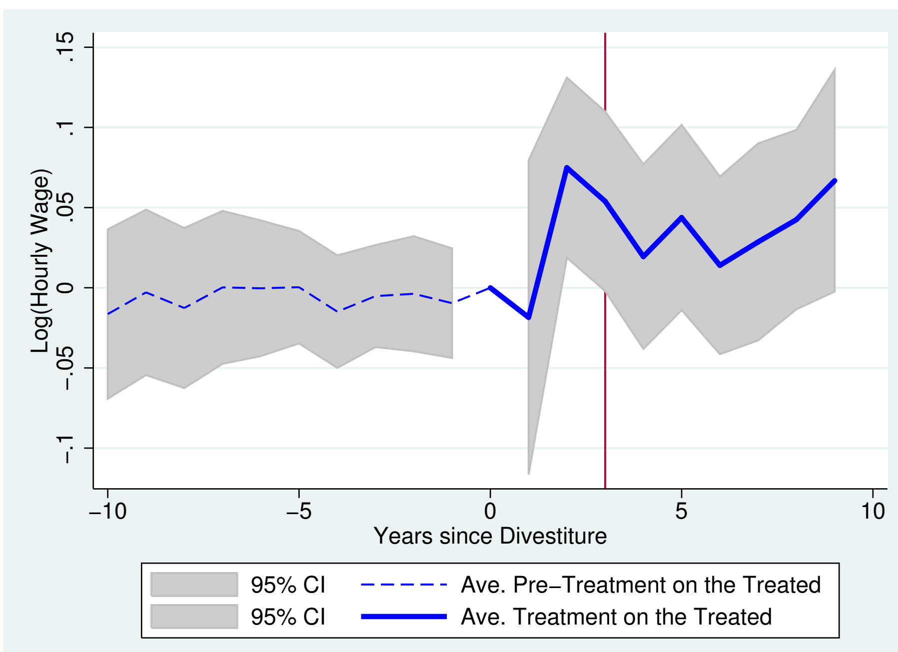
This paper uses two decades of detailed procurement data at gas- and coal-fired power plants to characterize the major determinants of regulatory inefficiency in U.S. electricity generation. I find evidence that asymmetric information, regulatory capture, and capital-bias all lead to substantial distortions in procurement decisions. I find the price of coal drops by 12% at deregulated plants relative to similar, nearby coal-fired facilities that were not subject to any regulatory change. Deregulated plants disproportionately switch to burning low-sulfur coal rather than install a capital-intensive abatement equipment to comply with environmental regulations, and expand imports from out of state by 25% if they were initially burning in-state coal. In addition, I find that the reallocation of procurement following divestiture is toward mines that are substantially more

Figure 1.15: *Matching by Year from Divestiture: Mine Labor, 10 nearest neighbors*

(a) *Log(Hours per MMBTU)*



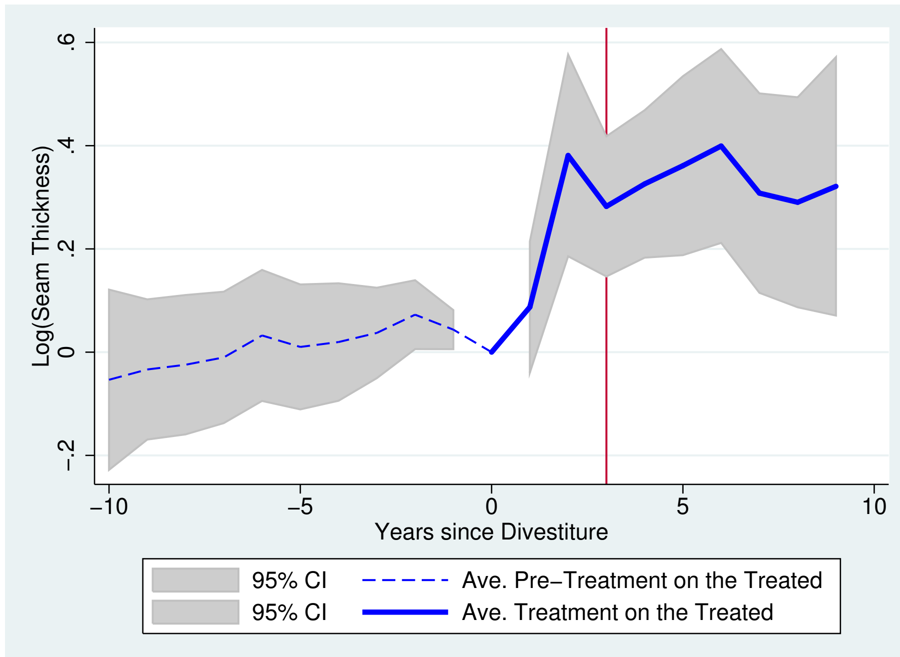
(b) *Log(Hourly Wage)*



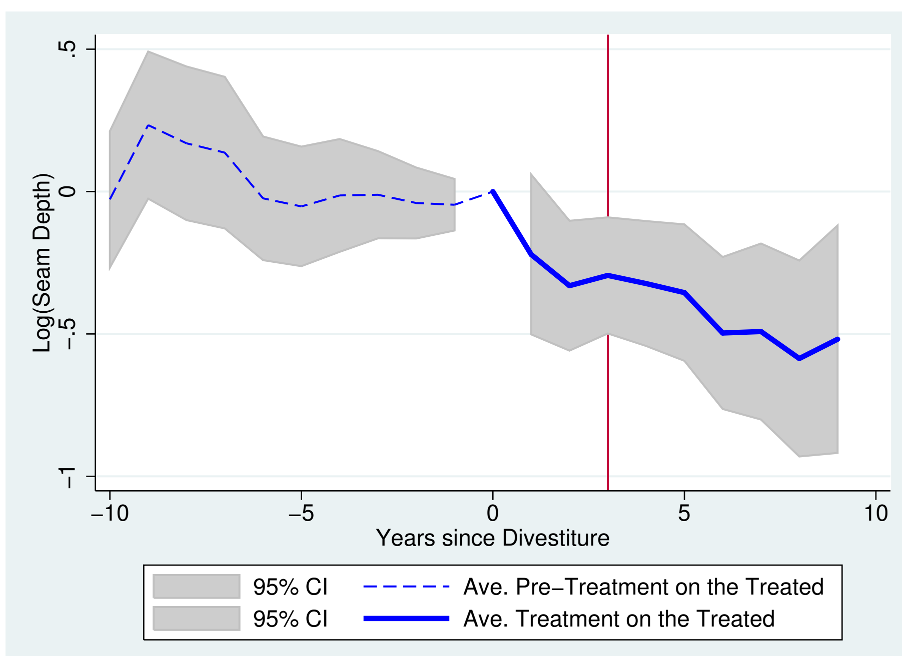
Note: *Hours per MMBTU* is the number of hours of labor required to extract $1MMBTU$ worth of coal at the mines from which matched plants purchase coal. Non-Divested facilities receive weight $\frac{1}{m_j}$ for each matched divested facility j. Matching criteria: $m = 10$, burning the same rank of coal in 1997, subject to the constraint that distance be less than 200 miles. Confidence intervals based on standard errors clustered by facility. The vertical line denotes the third year post-divestiture, the point at which most divested facilities resumed reporting fuel costs.

Figure 1.16: *Matching by Year from Divestiture: Source Mine Characteristics, 10 nearest neighbors*

(a) $Log(Seam\ Thickness)$



(b) $Log(Seam\ Depth)$



Note: *Seam Thickness* is the thickness and *Seam Depth* is the estimated depth below the surface of coal seams at the mines from which matched plants purchase coal. Non-Divested facilities receive weight $\frac{1}{m_j}$ for each matched divested facility j. Matching criteria: $m = 10$, burning the same rank of coal in 1997, subject to the constraint that distance be less than 200 miles. Confidence intervals based on standard errors clustered by facility. The vertical line denotes the third year post-divestiture, the point at which most divested facilities resumed reporting fuel costs.

productive than those who supply regulated facilities. In total, operators of divested coal-fired plants spend about $1B less per year on coal due to deregulation. These plants make up only 25% of coal-fired capacity, while the rest have continued operating without any change in regulation.

My results do not imply the universal failure of regulators to induce efficient behavior in the regulated community: I find that generators pay the same price for natural gas regardless of their regulatory status. Instead, this indicates that regulation may work well when the regulated community is unable to shroud its inefficient behavior from oversight.

After thirty years of deregulation, the pendulum is swinging back toward greater government oversight in order to correct market failures in critical sectors of the American economy such as finance, banking, and health care. In addition, the deregulatory momentum of the 1990's has stalled in the electricity sector following the 2000-2001 crisis in California. Although regulation may appear at first to be the solution to imperfect markets, as eloquently described by Bastiat (1850), this is not the end of the story.

Chapter 2

Productive Versus Allocative Efficiency Gains from Market-Based Electricity Generation: A Potential Outcomes Approach

2.1 Introduction

How do the losses inflicted by imperfect markets compare with the losses due to imperfect regulations enacted to curb the exertion of market power? In this paper, I evaluate this question in the context of U.S. wholesale electricity markets, which have replaced command-and-control operations in some areas. Following recent market failures (in the finance sector, in particular) Stiglitz (2009) has proposed a "General Theory of Regulation" that posits "the diasters associated with unfettered markets at least provide a prima facie case for the desirability of *some* regulation." There is, however, no reason to suppose that the existence of a market failure is a sufficient condition to guantee that any amount of regulation will improve social welfare.

Instead, optimal policy is determined by comparing the distortions under potential regulatory regimes, and minimizing the sum of market and regulatory losses. On this point, Stiglitz asserts that there has been, "no persuasive 'counterfactual' analysis constrasting what a world without regulation might look like as compared to the current regime." This paper undertakes such an evaluation in a major U.S. industry whose rocky relationship with deregulation has left even the Cato Institute waxing nostalgic about cost-of-service regulation (Van Doren and Taylor (2004)).

I construct a detailed monthly panel on the operations of U.S. generating facilities from 1990-2009. I connect this data to information on the mechanism through which plants are chosen to operate to meet demand. Because storage of electricity is largely impossible, generating capacity must exceed *peak* demand in order to avoid black-outs. System operators must therefore choose among the available plants (whose costs are heterogeneous) to meet the demand for electricity. Historically, these decisions have been made by the vertically-integrated Investor-Owned Utility (IOU) who has an exclusive license to operate in a given service territory. This has resulted in roughly 150 "Power Control Areas" (PCA) that largely rely on the generating assets within the service territory to satisfy local demand. In contrast to such command-and-control dispatch, regional wholesale electricity markets require generators to submit bids in auctions in order to produce.

To evaluate how the introduction of market-based dispatch has changed overall production costs, I use plant-month-fuel level data to estimate electricity production functions using the proxy methodology of Olley and Pakes (1996) and Levinsohn and Petrin (2003). This allows me to decompose fuel costs in to productivity and allocative efficiency components using the Olley-Pakes index. I then perform a differences-in-differences analysis on the derived productivity estimates. I also estimate how the relationship between output and average marginal fuel costs has changed since the introduction of market dispatch in a similar framework. I can therefore reconstruct the components of the Olley-Pakes index, except that my estimates explictly account for permanent differences between market and non-market areas, as well as common transitory shocks in order to isolate the causal effect of market dispatch on each of these components of overall average fuel costs. I find that while within-plant productivity changes have been minimal, the improved allocative performance of markets has lowered the average fossil-fuel production cost by over 15%. Inferences based on the Olley-Pakes index would overstate these gains.

The structure of the paper is as follows: in the next section I describe the structure of electricity generation and transmission in the United States, and the institutional details that will facilitate estimation. The third section describes the methods I use to estimate unobserved productivity, and the counterfactual framework that will utilize the derived parameters. The fourth section describes the data. The fifth section presents the results of my analysis, and the final section concludes.

2.2 Background on Power Control Areas and Dispatch in the United States

The U.S. electricity grid developed over the 20^{th} century based on a mix of IOUs, government-owned utilities (municipal, state, and federal), and non-profit cooperatives. All of these organizations tended to be vertically integrated, so they owned the power plants, the transmission system, and the delivery network within their respective, exclusively operated territories. The entity that determines which power plants operate to meet demand is called a "Balancing Authority." A single Balancing Authority controls the transmission system and dispatches power plants within a "Power Control Area." When vertically-integrated, the Balancing Authority and Utility have often been one-in-the-same, as with the service territory and Power Control Area.[1] While operating with relative autonomy, flows across PCAs are facilitated by transmission lines that connect areas.

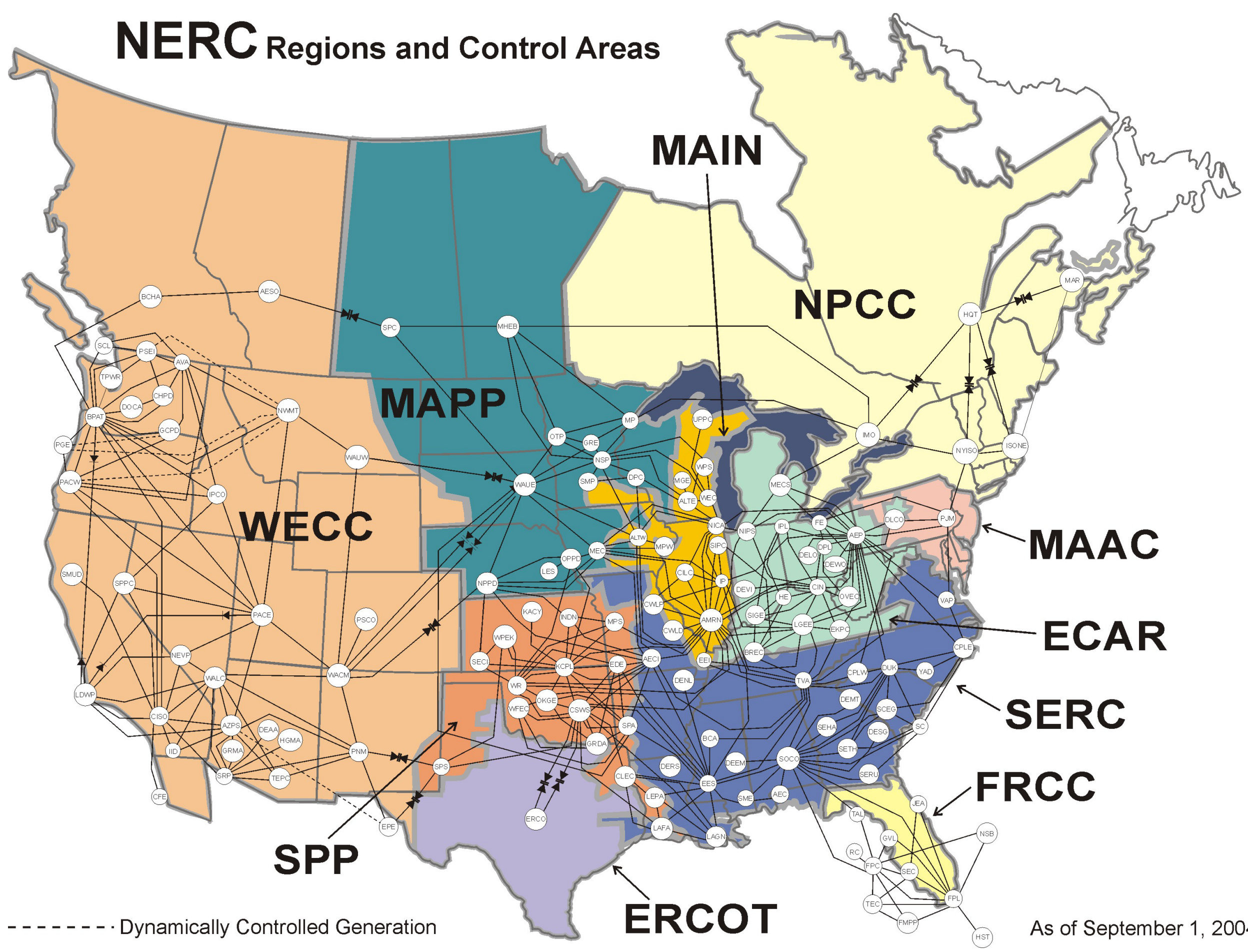
The national grid consists of three large Interconnections: East, West, and Texas–with relatively little capacity to transmit power between them. Figure 2.1 shows the configuration of the U.S. Electricity Grid in 2004.[2] The boundaries between Interconnections are denoted by the bowtie-shaped opposing arrows. The colored areas denote reliability regions who coordinate their operations (when large plants go down for maintenance, for example) in order to preserve the stability of the transmission system. The tangle of power control areas reflects the legacy of local monopolies that have been the principal architects of the U.S. electricity grid.

Although the Public Utility Regulatory Policies Act of 1978 (PURPA) opened the door for independent power generation (by requiring IOUs to buy their output at "avoided cost"), the growth of such producers was impeded by discriminatory transmission practices. Because the

[1]Exceptions include the New York and New England Power Pools, which formed in response to The Great Northeast Blackout of 1965, as well as smaller utilities that do not control dispatch directly.

[2]This is the earliest map available from NERC. It already includes the consolidation of Texas PCAs in to ERCOT, the formation of the PJM, and its expansion to include the former Allegheny PCA.

Figure 2.1: *U.S. Electricity Grid in 2004*



IOUs owned the transmission system, they could effectively shut independent producers out of wider markets by denying access.[3] This began to change with the Energy Policy Act of 1992, which required the functional separation of transmission system owners and power marketers–they were no longer allowed to use their wires to prevent or extract the surplus from trades across their territory. These changes were codified on April 24, 1996 with FERC orders 888 and 889, which required open-access, non-discriminatory tariffs for wholesale electricity transmission.

Open-access created greater potential for wholesale electricity markets, which were initially conducted through bilateral contracts for power. In this decentralized setting, contracts would typically specify the amount of electricity to be generated by one utility under a set of conditions, transmitted across a particular area, and withdrawn from the system by the purchasing utility. Mansur and White (2012) given examples showing why the nature of congestion in electricity transmission networks renders decentralized markets particularly poorly suited for identifying all of the potential gains from trade. In particular, transmission lines are constrained by net flows, not gross flows, as is the case in highway congestion, for example. When this is the case, there are production externalities that may allow otherwise infeasible bilateral trades to occur. Identifying these potential trades in a decentralized market is a challenge akin to coordinating simultaneous multilateral exchanges (Roth, Sönmez, and Ünver (2004)).

Operationally, balancing authorities have relied on engineering estimates of costs to devise dispatch algorithms to determine which plants within the power control area operate, and separately schedule any other operations requested by utilities (for bilateral trades). Centralized wholesale electricity markets work by integrating dispatch operations in to an auction for electricity. In day-ahead auctions, for example, generators submit bids to produce electricity, and only those below the price needed to meet projected demand are called on to operate. These auction incorporate feasibility constraints, so calling on higher-priced units to operate due to transmission congestion allows for the direct revelation of the cost of shortcomings in the transmission system.[4]

The transition from command-and-control to market dispatch is related to, but distinct from the

[3]Examples of IOUs exercising market dominace can be found in Appendix C of FERC Order 888.

[4]In particular, auctions using the "Standard Market Design" yield "Locational Marginal Prices" (LMPs) which denote the market-clearing price at each of the points of withdrawal from the system. When LMPs are identical everywhere, the system is said to be uncongested.

movement toward restructured electricity markets in the United States. In particular, the changes to dispatch and transmission described thus far were undertaken by the Federal government.[5] The end of cost-of-service regulation of vertically-integrated IOUs was initiated by states. It is important to distinguish between these developments, for although all states that adopted restructuring legislation eventually began participation in regional wholesale electricity markets, many areas began participating in these markets while preserving their traditional regulatory framework.[6]

The California Energy Crisis struck essentially in the middle of state-level restructuring efforts. Although every state in the Union had adopted or was considering restructuring legislation at the time, no state has restructured their electricity industry since the crisis, and a few states have repealed their legislation. The California crisis also slowed, but did not completely cease the formation of regional wholesale electricity markets. As a result, many areas in the United States currently operate in the same manner as they ever have, virtually untouched by the recent reforms. This sort of 'natural experiment' forms the basis of my empirical strategy by allowing me to compare changes in productive efficiency of otherwise identical generation facilities across regulatory regimes, as well as changes in the allocative efficiency of similar balancing authorities after ceding authority to a centralized market.

A handful of existing studies on electricity restructuring have focused on operational efficiency gains holding a given plant's level of output fixed (see, for example, Fabrizio, Rose, and Wolfram (2007); Bushnell and Wolfram (2005); Davis and Wolfram (2012); Cropper, Limonov, Kabir, and Anoop (2011); Cicala (2012)). Results on productive efficiency changes have been disappointing: it appears restructuring has had minimal impact on facility heat rates, for example. Research on allocative efficiency has focused primarily on loses due to the exercise of market power (see Mansur (2001, 2008); Borenstein, Bushnell, and Wolak (2002); Wolak (2012); Bushnell, Mansur, and Savaria (2007); Joskow, Kahn, and Economics (2002)). A notable exception is Mansur and White

[5]The ERCOT system in Texas is the exception because this Interconnection does not cross state lines, and is therefore not subject to FERC jurisdiction on many matters. However, Texas does participates in the North American Electric Reliability Corporation (NERC), which has been designated by FERC as the electricity reliability organization for the United States. Separating ERCOT from FERC rules yields distinctions without a difference.

[6]Examples include Indiana, West Virgina, and parts of Kentucky in the Pennsyvania-Jersey-Maryland (PJM) Interconnection, most of the Midwest ISO (MISO), and all of the Southwest Power Pool (SPP).

(2012), who compare the allocative efficiency of bilateral to centralized electricity markets, finding large welfare gains associated with one of the PJM expansions.

While market imperfections are certainly cause for concern, evidence of their existence is not proof of their inferiority. The relevant question for policymakers considering what to do about the current regulatory stalemate is: do markets (including all of their flaws) outperform the alternative methods for deciding which plants should operate in order to satisfy demand for electricity?

2.3 Methodology

To produce a given level of output industry-wide, cost reductions can come from two sources: productivity improvements that hold the distribution of output across facilities constant, or a shift of output between facilities that differ in their productivity. Prior studies on US electricity restructuring have focused on the former of these types of cost reduction (Fabrizio, Rose, and Wolfram (2007), Davis and Wolfram (2012), Bushnell and Wolfram (2005), Cropper, Limonov, Kabir, and Anoop (2011)). Estimating the distinction between these two sources of improvements in the telecommunications industry was the primary motivation that gave us the now widely used methodology for production function estimation in Olley and Pakes (1996) (henceforth OP). The reallocation of output to more productive firms within industries has been recognized as a fundamental source of gains from opening up to international trade (see Melitz (2003) and subsequent literature, and Pavcnik (2002) for an application of the OP estimator to the international trade setting).

To facilitate the decomposition of costs in the electricity sector, I assume the production function of electricity generating units that is similar to that of Fabrizio, Rose, and Wolfram (2007). Output is Leontief in fuel, complemented with labor and materials, while the production frontier is Cobb-Douglas in each of these inputs for a given level of output[7]. In logs,

$$y_{it} = \beta_0 + \min\{\beta_h h_{it}, \beta_l l_{it}\} + \beta_k k_{it} + \beta_a a_{it} + \omega_{it} + \varepsilon_{it}, \tag{2.1}$$

where y_{it} denotes the (log) output of generating unit i in month t. h, k, a, l, and m stand for

[7]For similar specifications, see Benkard (2000) for an application to learning in wide-body aircraft production, and Van Biesebroeck (2003) for automobile assembly.

fuel input in MMBTU (heat), characteristics of the capital stock (firing type, generator capacity, etc.), unit age, labor and materials, respectively. ε_{it} and ν_{it} are mean-zero transitory shocks to productivity that are orthogonal to the inputs and unobserved to both the econometrician and the plant manager when making production decisions. For expositional convenience I assume ω_{it} is a time-varying Hicks-neutral producitivity variable common to both Leontief arguments, though in fact our interpretation when studying fuel demand in the absence of data on labor or materials is that ω_{it} is the sum of a Hicks-neutral and fuel-biased productivity index that cannot be separately identified. This production function allows for the conversion of fuel to electricity to depend upon the capital stock at the plant (for example, the presence of abatement equipment (time-varying), or differing boiler specifications (fixed)), but rules out the substitutability of labor and materials for fuel.

2.3.1 Structural Estimation of Electricity Production Functions

Since at least Marschak and Andrews Jr (1944), econometricians have recognized the potential for simultaneity bias in production function estimation when plant managers make production decisions based on productivity that is unobserved to the econometrician: a positive shock to productivity is likely to be met with expanded input demand and production, which biases the factor demand coefficients. Estimation may also suffer from selection bias when plant managers make entry/exit decisions based on unobserved productivity. While permanent exit from electricity generation is rare, seasonal fluctuations in demand cause many units to go months on 'cold standby'. Estimating a logarithmic production function causes idle months to drop out of the data. The fact that less productive facilities are more likely to spend time off-line creates the potential for selection bias.

Instruments that are correlated with input demand, but are outside the production function and uncorrelated with unobserved productivity may help address simultaneity bias, but require meaningful variation across plants and over time. Such variation is rare in settings with national input and output markets. Instrumental variables also fail to account for selection bias. If firm heterogeneity is time-invariant, fixed effects may help solve the selection problem, but soak up much of the variance needed to identify coefficients on relatively fixed inputs. Selection bias will continue to cause problems if unobserved productivity varies over time.[8]

To account for time-varying heterogeneity and simultaneity in a single procedure, Olley and Pakes (1996) (OP) develop a semiparametric estimation algorithm embedded in a structural framework of firm behavior. In order to decompose the productive and allocative efficiency changes in electrical generation, I estimate a production function for electricity generation using an algorithm that extends recent work in the OP tradition, developed by Levinsohn and Petrin (2003), Ackerberg, Caves, and Frazer (2006), and summarized in Ackerberg, Benkard, Berry, and Pakes (2007) (ABBP).

The operating environment for generating facilities is similar to that of OP, and follows the notation of ABBP: plant managers are assumed to make production decisions on a per-period basis (monthly) in order to maximize current and expected discounted value of profits.[9] Given the need to schedule staff and order fuel for delivery, managers are assumed to make entry/exit decisions in advance of actual production. Per-period profits depend on a vector of unit-specific state variables: $(k_{it}, a_{it}, \omega_{it}, \Delta_t)$, where Δ_t refers to a measure of the market environment, including demand, factor prices, and state variables of all firms in the market.

In each period plant managers must decide whether to produce electricity or shutdown and receive payoff value $\Phi(k_{it}, a_{it}, \omega_{it}, \Delta_t)$. Shutting down may simply entail going on "cold standby", and is not necessarily permanent.[10] For our purposes, entry and exit will refer to the decision to start up or shut down production contingent upon the plant's existence. If a unit is operational, the manager decides on levels of variable inputs, including labor, materials, and fuel, based on the realized state variables to maximize profits. While most capital inputs are fixed upon construction of the generating unit (only 0.5% of plant-month observations record a change in generating capacity after birth), investment decisions for capital such as the addition of abatement equipment

[8]See Ackerberg, Benkard, Berry, and Pakes (2007) for a more complete discussion.

[9]Defining a general profit function allows specific payoffs to differ between regulated and unregulated plants. The key restriction, as explained below, is that the profit function of Investor-Owned Utilities to not deviate so drastically from standard cost-minimizing behavior as to reverse the typically positive relationship between productivity and optimum factor demands.

[10]See Cullen (2011) for a dynamic model of generating unit production designed to measure start-up and operating costs based on high-frequency (15 minute) production decisions. Pakes, Ostrovsky, and Berry (2007), Bajari, Benkard, and Levin (2007) and the literature cited in ABBP develop models that focus on entry/exit decisions to measure sunk costs and sell-off values in dynamic, multi-agent settings. For our purposes, start up and shut down decisions conditional upon plant construction are sufficient to identify unobserved productivity for production function estimates.

are made after revelation of period t state variables, and the associated changes to the capital stock appear in period $t+1$. State variables observed by the econometrician therefore evolve according to

$$\begin{aligned} k_{it+1} &= (1-\delta)k_{it} + i_t \\ a_{t+1} &= a_t + 1 \end{aligned}$$

Productivity (ω_{it}) is assumed to be observed by the plant manager before making production and investment decisions, but is unobserved by the econometrician. It is assumed to evolve according to a first-order Markov process:

$$p(\omega_{it+1}|\{\omega_{i\tau}\}_{\tau=0}^{t}, I_{it}) = p(\omega_{it+1}|\omega_{it}) \tag{2.2}$$

As emphasized in the modern production function literature, this is both an econometric and an economic assumption. It states that the distribution of next period's productivity given the information available to the plant manager at time t (denoted I_{it}) is completely determined by the current value of the productivity index. We additionally assume that $p(\omega_{it+1}|\omega_{it})$ is stochastically increasing in current productivity, i.e. ω_{it+1} is drawn from a more favorable distribution for units that are currently more productive. This ensures the monotonicity required for a unique solution to the Bellman equation that describes the plant manager's maximization problem:

$$V(k_{it}, a_{it}, \omega_{it}, \Delta_t) =$$

$$\max\{ \begin{array}{ll} \Phi(k_{it}, a_{it}, \omega_{it}, \Delta_t), & \max_{i_{it}\geq 0}\{\pi(k_{it}, a_{it}, \omega_{it}, \Delta_t) - c(i_{it}, \Delta_t) + \\ & +E[V(k_{it+1}, a_{it+1}, \omega_{it+1}, \Delta_{t+1})|k_{it}, a_{it}, \omega_{it}, \Delta_t, i_{it}]\} \end{array} \} \tag{2.3}$$

While the assumption that $p(\omega_{it+1}|\omega_{it})$ is stochastically increasing in ω_{it} helps increase the gap between the value of exit and production as productivity rises, the necessary assumption is that $\Phi(k_{it}, a_{it}, \omega_{it}, \Delta_t)$ does not rise so quickly as to invalidate the existence of a single lower bound of productivity that determines the optimal exit rule:

$$\chi_{it} = \{ \begin{array}{ll} 1(\text{continue}) & \text{if } \omega_{it} \geq \bar{\omega}(k_{it}, a_{it}, \Delta_t) \\ 0(\text{exit}) & \text{otherwise} \end{array} \} \tag{2.4}$$

The solution to the optimization of investment given positive production in equation (2.3) yields an investment demand curve that plays a critical role in identificating ω_{it} in OP. In the case of electricity generation, major investments are typically chosen at the time of plant construction. Subsequent investments such as abatement equipment are usually forced upon the generator, violating the monotonicity of $i(k_{it}, a_{it}, \omega_{it}, \Delta_t)$ required in order to invert the investment function to infer productivity.[11] We therefore have a single variable input (fuel), relatively fixed capital, and no intermediate input from which to infer productivity as in Levinsohn and Petrin (2003). As a result, I subsume the constant β_0 in to the productivity term ω_{it}, and employ the procedure suggested by Ackerberg, Caves, and Frazer (2006) to estimate production from fuel and capital inputs as

$$y_{it} = \beta_h h_{it} + \beta_k k_{it} + \beta_a a_{it} + \omega_{it} + \varepsilon_{it} \tag{2.5}$$

The fact that plant managers know their value of ω_{it} when choosing fuel input levels means that we can write the (log) demand for fuel as a function of the state variables in period t (subsuming Δ_t into t for notational convenience, as in OP):

$$h_{it} = f_t(\omega_{it}, k_{it}, a_{it}) \tag{2.6}$$

The key assumption for identification is that demand for heat inputs is strictly increasing in ω_{it}. This assumption would be violated if, for example, a utility operating on a cost-plus basis decided to run its less efficient plants more often as a means of inflating expenses. This is assumption is unlikely to be violated as long as regulators do not completely abdicate their responsibility to monitor both the availability and costs of units. As long as they do so, this would be a particularly transparent means of inflating costs. So long as (2.6) is strictly monotonic in productivity, we can invert it for substitution in (2.5)

$$y_{it} = \beta_h h_{it} + \beta_k k_{it} + \beta_a a_{it} + f^{-1}(h_{it}, k_{it}, a_{it}) + \varepsilon_{it} \tag{2.7}$$

While none of the coefficients in (2.7) are identified at this point, it is possible to use a flexible polynomial approximation to isolate idiosyncratic shocks ε_{it} to form an estimate of the output

[11] Fowlie (2010) uses a random coefficients logit model to estimate the impact that restructuring has had on generator's choice of abatement strategies conditional upon being subject to market-based Ozone regulations.

anticipated by the plant manager at time t

$$\phi_t(h_{it}, k_{it}, a_{it}) = \beta_h h_{it} + \beta_k k_{it} + \beta_a a_{it} + \omega_{it}$$

In the second stage, we utilize our assumption that unobserved productivity follows a first order Markov process of to form moment conditions based on the information available to the plant manager at the time production decisions are made. In particular

$$\begin{aligned} \omega_{it} &= E[\omega_{it}|I_{it-1}] = E[\omega_{it}|\omega_{it-1}] + \xi_{it} && (2.8) \\ &= g(\omega_{it-1}) + \xi_{it} && (2.9) \end{aligned}$$

where ξ_{it} is uncorrelated with decisions made in period $t-1$ by definition. Since current period capital is determined by period $t-1$ investment decisions, and heat demand is not a dynamic factor across months, we can use k_{it}, a_{it} and h_{it-1} to form moment conditions with ξ_{it}. Formally,

$$\begin{aligned} E\left[\xi_{it}| \begin{array}{c} k_{it} \\ a_{it} \\ h_{it-1} \end{array}\right] &= 0, \\ E\left[\xi_{it} \cdot \begin{array}{c} k_{it} \\ a_{it} \\ h_{it-1} \end{array}\right] &= 0 && (2.10) \end{aligned}$$

Estimation in the second stage begins by predicting a value for unobserved productivity given a candidate parameter vector $\beta = [\beta_h, \beta_k, \beta_a]$,

$$\omega_{it}(\beta) = \hat{\phi}_{it} - \beta_h h_{it} - \beta_k k_{it} - \beta_a a_{it} \tag{2.11}$$

For the unanticipated productivity moment conditions, project $\omega_{it}(\beta)$ on a polynomial of $\omega_{it-1}(\beta)$ in order to predict $E[\omega_{it}(\beta)|\ \omega_{it-1}(\beta)]$, and form an estimate for $\xi_{it}(\beta)$ based on the residual. Following the suggestion of Wooldridge (2009), and extending the moments derived by

ACF, we now have two moments:

$$E\begin{bmatrix}\varepsilon_{it}|I_{it}\\ \xi_{it}|I_{it-1}\end{bmatrix}=E\begin{bmatrix}y_{it}-\beta_h h_{it}-\beta_k k_{it}-\beta_a a_{it}+f^{-1}(h_{it},k_{it},a_{it};\beta_{f,t})|I_{it}\\ f^{-1}(h_{it},k_{it},a_{it};\beta_{f,t})_{it}-g(f^{-1}(h_{it-1},k_{it-1},a_{it-1};\beta_{f,t-1});\beta_g)|I_{it-1}\end{bmatrix}=0$$

The parameter vector is estimated by minimizing the sample analogue of the moment conditions (2.10):

$$\arg\min_{\beta}\left[\frac{1}{T-1}\frac{1}{N}\sum_{t=2}^{T}\sum_{i}\left(\xi_{it}(\beta)\cdot\begin{array}{c}k_{it}\\ a_{it}\\ h_{it-1}\end{array}\right)^2\right]$$

Standard errors from this two-step procedure can be bootstrapped, or following the suggestion of Wooldridge (2009), moment conditions from the two steps can be estimated simultaneously, allowing for analytic standard errors, and increased precision by using the covariances of the errors across moments in the variance-covariance weight matrix of GMM estimation.

2.3.2 Accounting for Selection

The procedure described to this point does not account for the entry/exit decisions encapsulated in (2.4). When plant managers decide whether or not to produce based on their evaluation of ω_{it}, (2.5) will suffer from selection bias, as only units with $\omega_{it} > \bar{\omega}(k_{it}, a_{it}, \Delta_t)$ will be observed in the data. The vast majority in 2008 being produced by units commencing operation prior to 1997, one might think selection problems can safely be ignored, or remedied with fixed-effects. With monthly data, however, selection is potentially a serious concern due to the seasonal nature of electricity demand combined with the impossibility of storage. High-cost "peaking" units are generally only used during times of high demand, and the least productive units may only be used a few days a year, if any. That said, permanent exit is especially rare due to requirements for reserve capacity, the costly nature of introducing new generating assets, and the potential for lucrative generation on days of exceptionally high demand.

While Levinsohn and Petrin (2003) and Ackerberg, Caves, and Frazer (2006) prove identification when the variable input is the basis for the productivity inversion, it has not yet been shown these results hold in the presence of endogenous selection. When selection is present, the moment conditions in (2.10) are no longer valid because survival in period t depends on the realization of ξ_{it}. While OP estimate the coefficients on variable inputs in the first stage, and need only worry about selection until the second, this is not the case when inputs are the basis of the productivity inversion. Taking expectations of (2.5) based on information available to plant managers at $t-1$, unobserved productivity (and therefore input demand) suffer from selection bias. State variables determined at time $t-1$ and the idiosyncratic error term are unaffected by the exit decision.

$$E[y_{it}|I_{it-1}, \chi_{it} = 1] = \beta_h h_{it} + \beta_k k_{it} + \beta_a a_{it} + E[\omega_{it}|I_{it-1}, \chi_{it} = 1]$$

Starting with productivity, OP show we can invoke the exit rule to write expected unobserved productivity as[12]

$$E[\omega_{it}|I_{it-1}, \chi_{it} = 1] = E[\omega_{it}|I_{it-1}, \omega_{it} > \bar{\omega}_t(k_{it}, a_{it})]$$

Employing the Markov transition distribution from (2.2), time $t-1$ expectations of ω_{it} conditional upon survival in t can be written as

$$\begin{aligned} E[\omega_{it}|I_{it-1}, \omega_{it} &> \bar{\omega}_t(k_{it}, a_{it})] = \int_{\bar{\omega}_t(k_{it},a_{it})}^{\infty} \omega_{it} \frac{p(\omega_{it}|\omega_{it-1})}{\int_{\bar{\omega}_t(k_{it},a_{it})}^{\infty} p(\omega_{it}|\omega_{it-1})} d\omega_{it} \\ &= \tilde{g}[\omega_{it-1}, \bar{\omega}_t(k_{it}, a_{it})] \qquad (2.12) \end{aligned}$$

For some function $\tilde{g}()$. Since approximating the exit productivity with a polynomial in the state variables would interfere with the identification of β_a and β_k, OP suggest using the probability of exit conditional upon information available at time $t-1$ as a basis for inferring the value of the exit productivity. To see this, note the probability of production in period t can be written as a function of information available in $t-1$:

$$\begin{aligned} \Pr[\chi_{it} &= 1|I_{t-1}] = \Pr[\omega_{it} > \bar{\omega}_t(k_{it}, a_{it})|\omega_{it-1}, \bar{\omega}_t(k_{it}, a_{it})] \qquad (2.13) \\ &= \tilde{\varphi}_t(\omega_{it-1}, k_{it}, a_{it}) = \varphi_t(h_{it-1}, k_{it-1}, a_{it-1}, i_{it-1}) = P_{it} \end{aligned}$$

Where the penultimate equality follows from the inversion of the fuel demand equation (2.6) in period $t-1$, and the fact that period t state variables are set in period $t-1$. Since (2.13) expresses the probability of continuing as a function of ω_{it-1} and the exit rule, and the probability of exit is

[12] To save notation, the economic environment Δt is encompassed with the subscript on the exit rule $\bar{\omega}_t(k_{it}, a_{it})$, as in OP.

strictly increasing in $\bar{\omega}_t(k_{it}, a_{it})$, it is possible to invert (2.13) to express the $\bar{\omega}_t(k_{it}, a_{it})$ as a function of prior productivity and probability of exit in period t as long as there is positive density in the neighborhood of exit. We then substitute this expression for the exit productivity into (2.12) to obtain a function we can estimate with a 3^{rd} or 4^{th} order polynomial approximation :

$$\begin{aligned}\tilde{g}[\omega_{it-1}, \bar{\omega}_t(k_{it}, a_{it})] &= \tilde{g}[\omega_{it-1}, \bar{f}(\omega_{it-1}, P_{it})] \\ &= g_{\omega}(\omega_{it-1}, P_{it})\end{aligned}$$

In practice $\hat{P}_{it}$ is estimated using a polynomial expansion of $\varphi_t(h_{it-1}, k_{it-1}, a_{it-1}, i_{it-1})$ in a probit model, and $\omega_{it-1}(\beta)$ is identical to that of the second step of the algorithm in the absence of selection (2.11). While unanticipated productivity changes (ξ_{it}) violate the orthogonality conditions necessary to form moments in the presence of endogenous entry/exit, once this selection correction is applied it is possible to form moment conditions analogous to (2.10) based on ζ_{it}, the unanticipated productivity shock conditional upon survival:

$$\begin{aligned}\omega_{it} &= E[\omega_{it} | I_{it-1}, \omega_{it} > \bar{\omega}_t(k_{it}, a_{it})] + \zeta_{it} \\ &= g_{\omega}(\omega_{it-1}, P_{it}) + \zeta_{it}\end{aligned}$$

With this adjustment estimation proceeds based on two moment conditions in unanticipated shocks

$$E\begin{bmatrix} \varepsilon_{it} | I_{it} \\ \zeta_{it} | I_{it-1} \end{bmatrix} = 0 \tag{2.14}$$

The steps of the estimation algorithm follow those outlined in the case without selection, this time incorporating the probability of survival in the second stage to form the moment conditions.

2.3.3 Causal Estimation of Allocative Efficiency Gains

Structural estimation of the production function is useful for decomposing the components of cost changes in the electricity industry over the last 20 years. Whether or not market dispatch *caused* these changes hinges upon the construction of a counterfactual operating environment for firms in restructured markets. A structural analysis of this type would require a dynamic general equilibrium model of firm behavior that accounts for response to the economic/regulatory environment. It would also require an assumption on how the profit function differs across regulatory regimes. For a causal analysis this is self-defeating: the model must assume the (non)existence of behavior it was intended to test. I therefore focus the remainder of my analysis on the construction of a credible counterfactual to identify the changes in electricity production caused by restructuring.

Suppose that the productivity at plant i in month t can be expressed as a function of a plant-specific, time invariant component, a transitory component, and a value that depends upon how the plant is called-upon to generate electricity:

$$\omega_{it} = \theta_i I(plant = i)_{it} + \alpha_t I(month = t)_{it} + \tau I(dispatch = mkt)_{it} + \nu_{it} \tag{2.15}$$

Under these assumptions, applying a differences-in-differences framework to the derived productivity estimates allows for causal inference of the effect of markets based on the relative change in productivity between market and non-market facilities. This is similar to the work on heat rates in Bushnell and Wolfram (2005)–the key differences being the analysis of dispatch rather than regulator regime, and the inclusion of consistent productivity estimates rather than raw heat rates.

To evaluate the effect of markets on allocative efficiency, I estimate a rudimentary model of dispatch according to

$$\begin{aligned} Y_{it} &= \sum_{a=0}^{A}\sum_{t=0}^{T}\gamma_{at} I(Area_a, Month_t) + \beta_0 C_{it} + \sum_{t=0}^{T}\delta_t I(month_t) C_{it} + \\ &+ \beta_1 I(mkt)_{it} C_{it} + \beta_2 I(post * mkt)_{it} C_{it} + \epsilon_{it} \end{aligned} \tag{2.16}$$

where Y_{it} is the output plant i in area a is called on to produce in month t, and C_{it} is plant i's marginal fuel cost at time t. The area-by-month dummies ensure that the total electricity dispatched in the area is sufficient to meet demand, whatever the allocation across facilities. The β's in equation (2.16) measure the relationship between cost and output–effectively the residual demand curve facing each plant. The remaining terms impose a differences-in-differences reallocation of output among plants: β_0 measures the average slope of residual demand across all areas, the δ_t's allow this slope to vary over time, and β_1 allows for a time-invariant difference between the areas that adopted market dispatch, and those that preserved their balancing authority. β_2 measures the change in the relationship between cost and output after market adoption, relative to areas that did not change.

This model is designed to answer the question: How do markets reallocate output to lower cost plants? Market power will tend to increaseβ_2 as low-cost facilities withhold their output to drive up the cost of the marginal producer. However, β_2 will be negative if markets are superior at allocating output to low cost plants, even after netting out the distortions of market power. While Olley and Pakes (1996) simply consider the covariance between productivity and output as their measure of allocative efficiency (this is identical to the numerator in each of the β's), this framework introduces an explicit counterfactual in order to evaluate the effect of the introduction of markets.

2.4 Data

This paper uses a twenty-year panel of data on operations in the U.S. electricity sector, synthesized from a number of publicly-available sources. Because fuel prices became subject to non-disclosure for divested power plants, I also use restricted-access data from the Department of Energy for these facilities. To calculate the marginal fuel cost of electricity production, I combine data on fuel prices from Form EIA-423 with monthly facility-level data on heat input and net generation from 1990-2009 from the Department of Energy's Energy Information Administration (EIA) Forms EIA-759/906/923. This data also serves as the basis for analysis of allocative and productive efficiency gains, as it reports the output of essentially every source of electricity in the United States over this period.

I link power plants to market participation status by identifying the power control area in which the plant is located. This data comes from both EIA-861, as well as the eGRID database constructed by the Environmental Protection Agency (EPA).

To estimate the propensity score for selection correction, I utilize data on the demand for electricity from Form EIA-826, and local temperature data from NOAA's Integrated Surface Database during the sample period.

Tables 2.1 and 2.2 present the summary statistics of fossil-fuel-fired electricity generating facilities in the United States from 1990-1996, the year before any market-based dispatch operations began. Panel B of Table 2.2 summarizes the characteristics of recent entrants among gas-fired generating units in their initial year of operation, the only substantial capacity additions during the sample period. Power plants in areas that began market-based dispatch are different from their non-market counterparts on a number of dimensions. They tend to each have modestly lower generating capacities (and production) per plant across all fuel types, and continues to hold for recent gas-fired capacity additions. Capacity factors denote the share of total potential production if the plant had been operating at full capacity for the entire year. During this period, coal tends to provide base-load production, a combination of coal and gas "follow" the load over the course of the day, and the much more expensive oil-fired units are used sparingly. The vintage of plants reflects the costliness of building new coal-fired capacity since the Clean Air Act, and the relative expense of oil-derived electricity generation. Although the plants in these areas do differ from each other, aside from fuel costs (which can be isolated), it is unclear how these differences invalidate a comparison of changes in the allocation of production following the introduction of market-based dispatch.

2.5 Results

Production Function Estimates

Tables 2.3-2.5 present estimates of electricity production functions for each type of fossil fuel. The first two columns of each table present the results of ordinary least squares regressions of (logged) output on the relevant explanatory variables. The second two columns utilize an instrumental variables approach in which heat input is instrumented with demand, lagged heat input, and temperature data. The final two columns present results of the generalized method of moments strategy described in sub-section 2.3.1. For each estimation approach, the second column includes a correction for the probability of operating in a given month as described in sub-section 2.3.2. While production function estimates are mostly stable across specifications, there are a couple noteworthy features of these results. Simultaneity bias of variable inputs implies the coefficient on heat should be lower when unobserved productivity is taken in to account. In addition, the coefficient on capital (the nameplate capacity) should tend to be biased downwards as larger plants

Table 2.1: *Characteristics of Coal- and Oil-Fired Facilities 1990-1996*

A. Coal-Fired Facilities	Market Areas	No Market Areas	Difference of Means
Capacity (MW)	726.49	920.86	–194.37***
	[683.49]	[767.66]	(29.05)
Annual Net	3625.76	4699.65	–1073.89***
Generation (GWh)	[3887.87]	[4427.73]	(166.06)
Capacity Factor	0.50	0.54	–0.04***
	[0.20]	[0.19]	(0.01)
Plant Vintage	1962.22	1965.82	–3.59***
	[13.06]	[13.56]	(0.55)
Heat Rate	11.45	10.82	0.63***
(MMBTU/MW)	[2.05]	[2.33]	(0.09)
Fuel Price	1.36	1.45	–0.09***
($/MMBTU)	[0.42]	[0.41]	(0.02)
Sulfur Content	1.19	0.99	0.19***
(lbs/mmbtu)	[0.87]	[0.74]	(0.03)
Scrubbers	0.23	0.33	–0.10***
	[0.42]	[0.47]	(0.02)
NOx Abatement	0.20	0.28	–0.08***
	[0.40]	[0.45]	(0.02)
Facilities	343	142	485

B. Oil-Fired Facilities	Market Areas	No Market Areas	Difference of Means
Capacity (MW)	170.63	284.84	–114.20***
	[305.98]	[412.69]	(15.63)
Annual Net	166.66	333.56	–166.90***
Generation (GWh)	[595.31]	[872.41]	(31.35)
Capacity Factor	0.09	0.07	0.02**
	[0.19]	[0.15]	(0.01)
Plant Vintage	1964.76	1966.73	–1.97***
	[12.39]	[9.44]	(0.59)
Heat Rate	14.01	13.34	0.67**
(MMBTU/MW)	[5.85]	[4.87]	(0.26)
Fuel Price	1.59	2.09	–0.50***
($/MMBTU)	[1.93]	[1.98]	(0.09)
NOx Abatement	0.03	0.03	0.00
	[0.17]	[0.17]	(0.01)
Facilities	411	120	531

Note: Unweighted facility-level statistics presented. Standard deviations are in brackets, and facility-clustered standard errors in parentheses are from a regression on the treatment variable. * $p<0.1$, ** $p<0.05$, *** $p<0.01$

Table 2.2: *Characteristics of Gas-Facilities by 1996 Incumbency*

A. Incumbent Gas-Fired Facilities

	Market Areas	No Market Areas	Difference of Means
Capacity (MW)	316.18	342.71	–26.53
	[439.18]	[467.63]	(17.95)
Annual Net	584.71	618.96	–34.25
Generation (GWh)	[1172.46]	[1335.76]	(48.99)
Capacity Factor	0.10	0.10	0.00
	[0.19]	[0.17]	(0.01)
Plant Vintage	1962.75	1963.70	–0.95*
	[12.49]	[13.34]	(0.54)
Heat Rate	13.92	13.16	0.76***
(MMBTU/MW)	[7.47]	[3.95]	(0.27)
Fuel Price	2.48	2.41	0.06**
($/MMBTU)	[0.64]	[0.81]	(0.03)
Combined Cycle	0.05	0.11	–0.07***
(%)	[0.20]	[0.27]	(0.01)
NOx Abatement	0.06	0.04	0.02**
	[0.23]	[0.19]	(0.01)
Facilities	605	212	817

B. Entrant Gas-Fired Facilities

	Market Areas	No Market Areas	Difference of Means
Capacity (MW)	223.97	404.90	–180.92***
	[286.66]	[493.07]	(62.60)
Annual Net	509.29	664.87	–155.58
Generation (GWh)	[960.09]	[1015.57]	(162.36)
Capacity Factor	0.20	0.23	–0.03
	[0.34]	[0.35]	(0.06)
Plant Vintage	2001.30	2001.80	–0.50
	[2.03]	[2.33]	(0.36)
Heat Rate	11.50	11.10	0.41
(MMBTU/MW)	[4.94]	[6.62]	(0.93)
Fuel Price	5.07	4.75	0.32
($/MMBTU)	[1.98]	[1.72]	(0.31)
Combined Cycle	0.21	0.42	–0.21***
(%)	[0.41]	[0.50]	(0.07)
NOx Abatement	0.70	0.71	–0.01
	[0.46]	[0.46]	(0.08)
Facilities	96	59	155

Note: Unweighted facility-level statistics presented. Standard deviations are in brackets, and facility-clustered standard errors in parentheses are from a regression on the treatment variable. * $p<0.1$, ** $p<0.05$, *** $p<0.01$

Table 2.3: *Electricity Production Function Estimates: Coal-Fired*

	(1) OLS	(2) OLS	(3) IV	(4) IV	(5) OP/LP	(6) OP/LP
Heat Input	1.046	1.046	1.036	1.026	1.069	1.034
	(0.0004)	(0.0003)	(0.0006)	(0.0007)	(0.0019)	(0.0374)
Nameplate	0.029	0.061	0.039	0.066	0.047	0.011
Capacity	(0.0005)	(0.0020)	(0.0007)	(0.0020)	(0.0027)	(0.0029)
Facility Age	0.002	0.020	0.001	0.025	0.015	0.000
	(0.0005)	(0.0007)	(0.0005)	(0.0008)	(0.0011)	(0.0009)
Scrubber	–0.020	–0.032	–0.019	–0.033	0.006	–0.021
	(0.0005)	(0.0012)	(0.0005)	(0.0012)	(0.0011)	(0.0011)
NOx	0.011	–0.001	0.011	–0.001	–0.038	0.007
	(0.0008)	(0.0006)	(0.0008)	(0.0006)	(0.0035)	(0.0311)
Constant	–3.249	–3.514	–3.165	–3.270	–4.233	–3.476
	(0.0042)	(0.0133)	(0.0057)	(0.0151)	(0.0910)	(0.4838)
Selection Correction	No	Yes	No	Yes	No	Yes
Obs.	88432	88432	88432	88432	88432	88432

Note: Continuous independent variables are in logs. Standard errors in parentheses. Excluded states: AK,HI.

Table 2.4: *Electricity Production Function Estimates: Gas-Fired*

	(1) OLS	(2) OLS	(3) IV	(4) IV	(5) OP/LP	(6) OP/LP
Heat Input	1.039	1.030	1.040	1.030	1.028	1.028
	(0.0002)	(0.0002)	(0.0002)	(0.0003)	(0.0013)	(0.0014)
Nameplate	0.034	0.045	0.032	0.045	0.044	0.060
Capacity	(0.0003)	(0.0010)	(0.0003)	(0.0010)	(0.0013)	(0.0009)
Facility Age	–0.081	–0.008	–0.081	–0.008	–0.061	–0.055
	(0.0003)	(0.0007)	(0.0003)	(0.0007)	(0.0024)	(0.0010)
NOx	0.041	0.028	0.040	0.028	–0.008	–0.041
	(0.0014)	(0.0011)	(0.0014)	(0.0012)	(0.0007)	(0.0049)
Constant	–2.847	–3.028	–2.855	–3.033	–2.894	–2.682
	(0.0021)	(0.0060)	(0.0022)	(0.0064)	(0.0505)	(0.1428)
Selection Correction	No	Yes	No	Yes	No	Yes
Obs.	120867	120867	120867	120867	120867	120867

Note: Continuous independent variables are in logs. Standard errors in parentheses. Excluded states: AK,HI.

should be able to survive given lower productivity. These expected biases tend to hold when comparing OLS results with IV and GMM (and the role of the selection correction on nameplate), though it also appears as the production processes at generating facilities are sufficiently fixed that these are not tremendous sources of bias.

Table 2.5: *Electricity Production Function Estimates: Oil-Fired*

	(1) OLS	(2) OLS	(3) IV	(4) IV	(5) OP/LP	(6) OP/LP
Heat Input	0.997	0.989	1.001	1.000	0.994	0.993
	(0.0002)	(0.0002)	(0.0002)	(0.0005)	(0.0031)	(0.0039)
Nameplate	0.041	0.025	0.039	0.024	0.040	0.027
Capacity	(0.0002)	(0.0006)	(0.0003)	(0.0006)	(0.0012)	(0.0012)
Facility Age	–0.027	–0.044	–0.027	–0.042	–0.024	–0.026
	(0.0006)	(0.0009)	(0.0006)	(0.0009)	(0.0011)	(0.0019)
NOx	–0.039	–0.028	–0.045	–0.027	–0.037	–0.080
	(0.0025)	(0.0018)	(0.0025)	(0.0018)	(0.0068)	(0.0130)
Constant	–2.601	–2.378	–2.626	–2.478	–2.590	–2.610
	(0.0028)	(0.0045)	(0.0030)	(0.0061)	(0.0408)	(0.0273)
Selection Correction	No	Yes	No	Yes	No	Yes
Obs.	82300	82300	82300	82300	82300	82300

Note: Continuous independent variables are in logs. Standard errors in parentheses. Excluded states: AK,HI.

Olley-Pakes Decomposition of Production (Fuel) Costs with Heterogeneous Factor Prices

A common assumption for the analysis of allocative efficiency in papers employing the OP estimator is that factor prices are uniform across space, though they may vary over time. This allows one to analyse productivity changes as a sufficient statistic for changes in aggregate production costs. Heterogeneity of fuel type and transportation costs, however, yields widely varying heat input prices at any moment in time. An accounting of productivity changes that ignores heterogeneity of fuel costs is insufficient to make inferences regarding changes in production cost in this setting. Social gains are understated when output shifts to more productive firms that also have lower input costs, and will actually have the wrong sign when relative costs are greater than relative productivities.

I construct an index that converts productivity (in units of output) to fuel costs in order to account for heterogeneity of fuel prices when evaluating efficiency changes. That is, rather than studying trends in market-share weighted average industry productivity, $\overline{\omega}_t \equiv \sum_{i=1}^{n} s_{it}\omega_{it}$, I evaluate what I will refer to as the "Inverse Fuel Productivity," ψ_{it}, presented in dollar units:

$$\psi_{it} \quad \equiv \quad p_{it} \exp -\frac{1}{\beta_h}\omega_{it}$$

where p_{it} is the price of fuel per MMBTU. The analogous market-share weighted average, $\overline{\psi}_t \equiv \sum_{i=1}^{n} s_{it}\psi_{it}$ can be decomposed in to an across-facility average, and the covariance between inverse fuel productivity and market share, as in the OP index:

$$\overline{\psi}_t = \frac{1}{n}\sum_{i=1}^{n} \psi_{it} + cov(s_{it}, \psi_{it})$$

Figures 2.2-2.4 display how inverse fuel productivity has changed over time by fuel type and eventual market participation. Although these indicies were almost identical through 2000, a gap has opened up between market and non-market areas, particularly since 2004 (which corresponds with the introduction of MISO and expansion of PJM). The relative gain for market areas has been driven almost entirely by changes in coal-fired facility operations, though it is worth noting the underperformance of gas in 2000-2001, corresponding to the California electricity crisis. The utility of this type of decomposition is immediately clear by comparing Figures 2.3 and 2.4: there has been essentially no change in the across-facility averages, while there has been a large shift in how high-cost plants are punished with reduced output in market areas. It must be kept in mind, however, that this is simply a decomposition of averages–nothing in this framework allows one to attribute changes to the introduction of markets, as no counterfactual has been posed.

Within-Facility Productivity Changes

As discussed earlier, a number of studies have evaluated the impact that restructuring of the electricity sector has had on productive efficiency. Here I apply the methods used in many of these studies to evaluate how the introduction of market-based dispatch has affected changes in within-plant productive efficiency. There are two components of average fuel cost to produce an additional megawatt-hour of electricity: the heat rate, and the price of fuel. Table 2.6 presents the results of applying a differences-in-differences framework on the productivity parameters estimated earlier, as in Pavcnik (2002), and on fuel prices themselves. Because transportation costs introduce geographic-specific, time-varying unobservables that might bias results, all estimates include Census Division-by-Year fixed effects. These have been shown in Cicala (2012) to give

Figure 2.2: *Inverse Fuel Productivity by Dispatch Method, Weighted by Quantity*

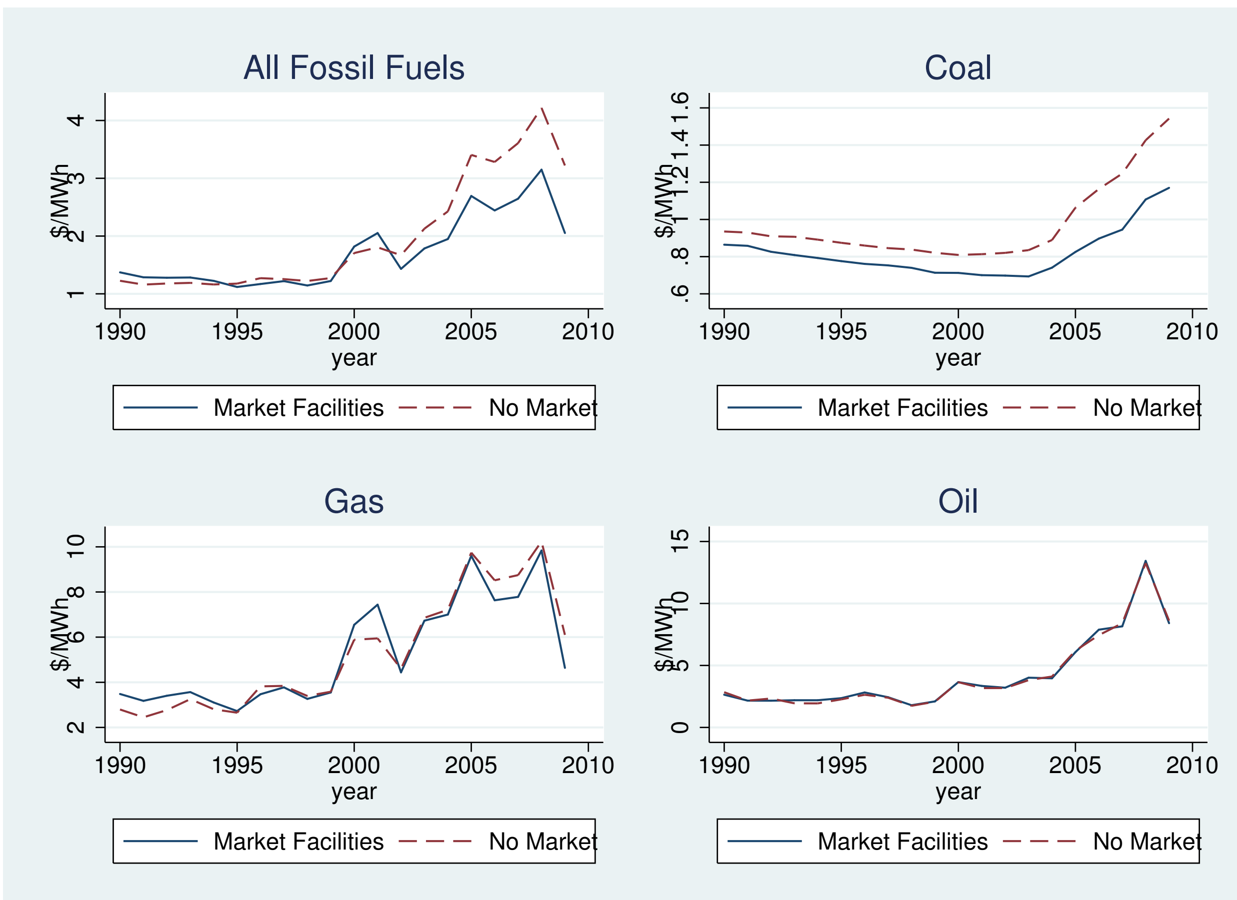


Figure 2.3: *Across-Plant Inverse Fuel Productivity by Dispatch Method, Unweighted*

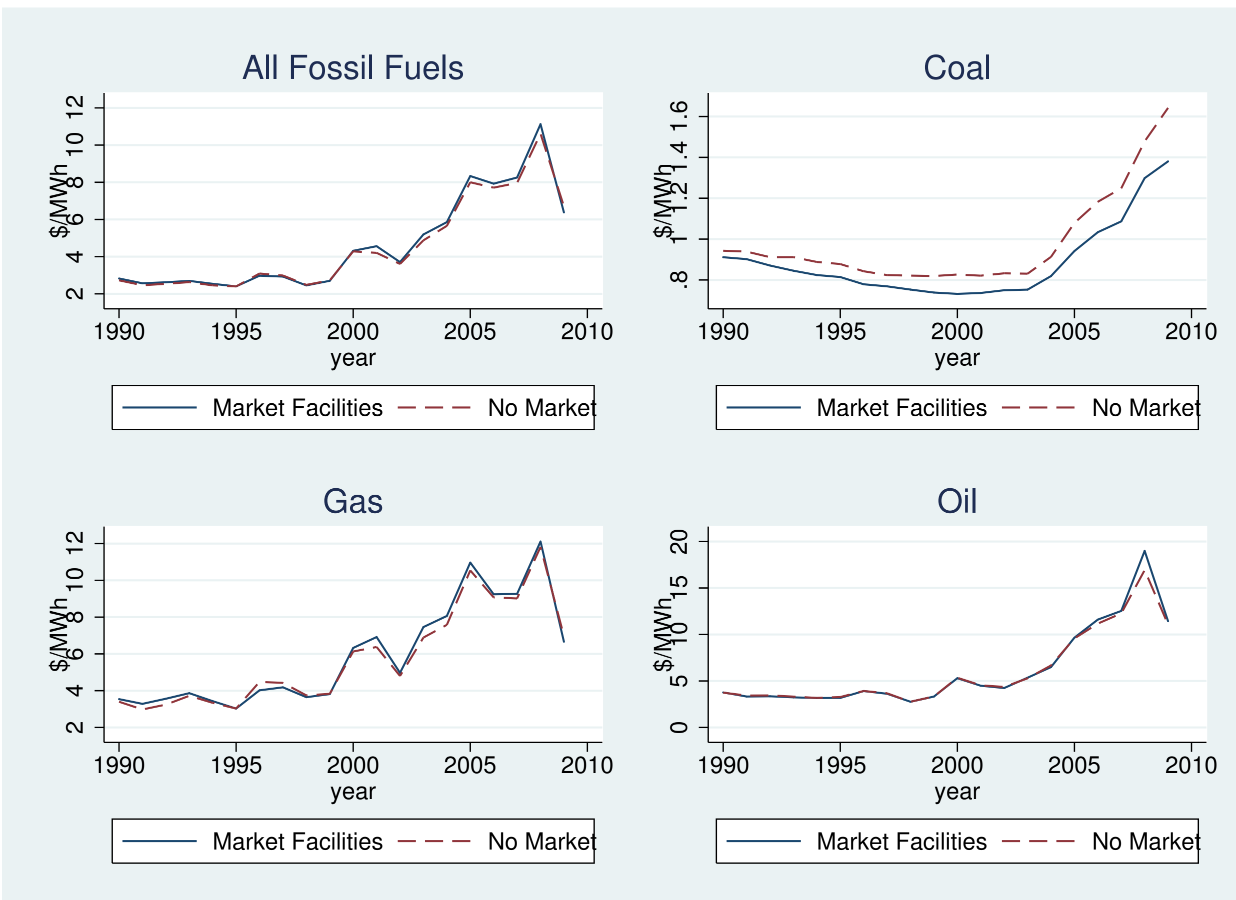


Figure 2.4: *Covariance Between Inverse Fuel Productivity and Production Share by Dispatch Method*

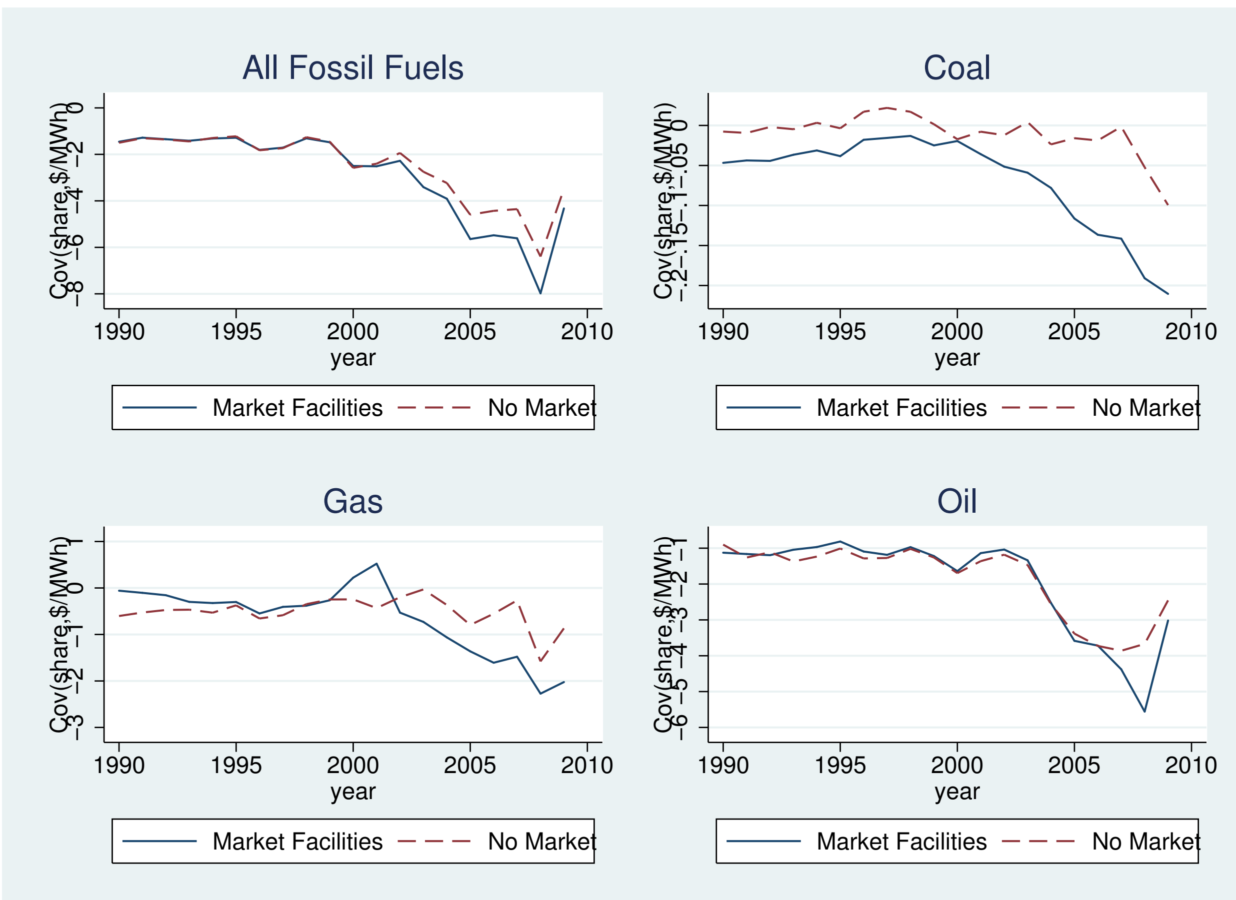


Table 2.6: *Difference-in-Differences Estimates of Market Dispatch on Plant Productivity*

A. Fuel Productivity	(1) Coal	(2) Gas	(3) Oil
Post x Market	–0.002	–0.007*	–0.004
	(0.003)	(0.004)	(0.003)
Mean	0.51	–0.23	0.11
R^2	0.615	0.592	0.686
Facilities	414	1160	1032
Obs.	89984	133789	99422

B. Fuel Prices	(1)	(2)	(3)
Post x Market	–0.068**	0.198	0.604***
	(0.028)	(0.136)	(0.149)
Mean	1.79	7.31	13.21
R^2	0.751	0.476	0.829
Facilities	407	935	694
Obs.	82917	94347	50014

Note: All specifications include Facility and Census Division-Year. Panel B only includes months in which fuel was delivered. Mean of the dependent variable is presented for the post-treatment observations. Standard errors clustered by facility in parentheses. Excluded states: AK,HI. * p<0.1, ** p<0.05, *** p<0.01

results similar to a more sophisticated geographic matching estimator.[13]

Table 2.6 presents the results of this analysis. As in Fabrizio, Rose, and Wolfram (2007); Bushnell and Wolfram (2005), I do not find much flexibility in terms of heat rates at generating facilities. For prices, there is a small decrease in the price of coal, no change for natural gas, and an anomalous *increase* in the price of oil at market-dispatched facilities. It is unclear what could give rise to such an increase, but is worth looking in to in future work.

Counterfactual Production Costs Using a Differences-in-Differences Dispatch Model

Table 2.7 presents the results of estimating the relationship between output and marginal costs in the difference-in-difference framework of equation (2.16). As discussed in sub-section 2.3.3, this

[13]It is worth noting that the results here do not contradict those in Cicala (2012) because many areas that adopted market dispatch remain rate-regulated. It is therefore important to distinguish between the incentives of plants based on the regulatory framework they face.

Table 2.7: *Difference-in-Differences Estimates of Marginal Fuel Cost on Plant Output*

	(1) All Fossil	(2) Coal	(3) Gas	(4) Oil
Post x Market	–0.142*	–4.953***	–0.082**	–0.097***
	(0.0771)	(0.5692)	(0.0413)	(0.0153)
Market	0.895***	10.438***	0.579***	0.097***
	(0.0800)	(0.9056)	(0.0687)	(0.0258)
Marginal Cost	–10.242***	–54.363***	–3.993**	–0.508**
	(1.1236)	(5.9399)	(1.5574)	(0.2524)
R^2	0.293	0.348	0.319	0.324
Obs.	323195	89984	133789	99422

Note: Dependent Variable is monthly net-generation in GWh. Coefficients are interacted with average marginal fuel cost. Standard errors clustered at Power Control Area-Month in parentheses.

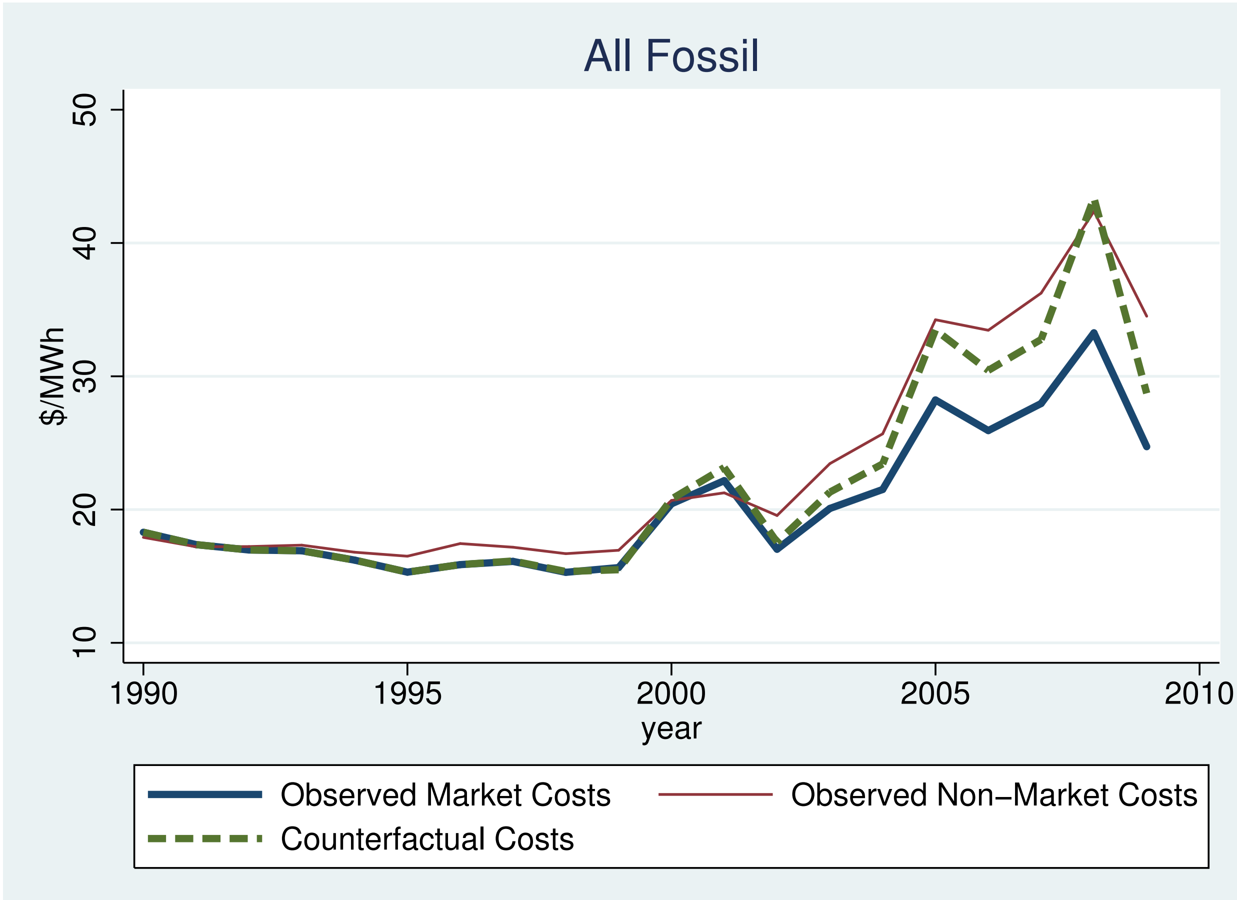
framework includes the flavor of the OP index because the numerator of the coefficient of output on marginal costs is exactly the allocative efficiency component of the index. The value-added here is that equation (2.16) is explicity about the counterfactual: it allows time-invariant differences in the relationship between costs and output to exist (due to transmission infrastructure, for example), while also exploiting the staggered timing of market introductions to remove common transitory shocks to be separated out from the impact of markets.

There is a strong negative overall relationship between average marginal costs and output (which is reassuring). Interestingly, market areas have historically not punished higher costs with less output quite as much as in non-market areas. However, there is a common shift across fossil fuels that further penalizes increased fuel costs with reduced output after the introduction of market dispatch.

We have estimated the components of average marginal fuel costs necessary to predict what costs would have prevailed in the absence of market dispatch. Counterfactual heat rates are predicted by plugging $\overline{\omega}_t(0)$ in for the estimated productivity of plants subject to market dispatch, $\omega_{it}(1)$. Counterfactual fuel prices are similarly computed by subtracting the estimated effect of markets from the price of deliveries to plants under market dispatch. The product of these two yields the counterfactual unweighted across-plant average component of the OP index, with the critical distinction that the interpretation of the difference between observed market costs and predicted costs is causal.

The full counterfactual estimate of what overall costs would have prevailed in the absence

Figure 2.5: *Observed Average Fuel Costs versus Estimated Counterfactual in Absence of Market Dispatch*



of markets is computed by weighting the counterfactual marginal fuel costs by the quantities predicted by equation (2.16).[14] Figure 2.5 plots the production-weighted average fossil fuel costs by dispatch method, but now also includes the predicted costs that would have prevailed in the market areas if not for the change in dispatch mechanism. It shows that an inference of the benefits of market dispatch based on a simple comparison of market and non-market areas would often lead to an overstatement. The estimated counterfactual suggests that fossil fuel costs are 15-20% lower due to the superior allocation of production under market dispatch. While it is possible to separate out the components of productivity and allocative efficiency (using either observed or counterfactual quantities), in this setting the productivity results are so small as to essentially duplicate the lines at each allocation.

[14]In practice, I estimate (2.16) allowing for heterogeneous coefficients for fuel type and bins for nameplate generating capacity. This allows for dispatch consideration of ramping, and helps the counterfactual predictions obey production capacity constraints.

2.6 Conclusion

How has the introduction of market-based dispatch affected the cost meeting the demand for electricity? Although the dangers of market power have been well-studied in this setting, a complete accounting has been missing. In this paper, I use the recent introduction of wholesale electricity markets in some areas as a natural experiment to evaluate the performance of markets relative to the policy-relevant counterfactual: centralized dispatch by a regulated local monopolist. I construct a twenty-year panel of data on US electricity generation costs and the mechanisms used to allocate production to plants. I use proxy methods based on Olley and Pakes (1996); Levinsohn and Petrin (2003) to estimate fuel-specific production functions, and construct the Olley-Pakes index of productivity to decompose costs in to within-plant productivity changes and allocative efficiency changes.

I then apply a potential outcomes framework to the derived productivity estimates, allowing the construction of counterfactual costs that explicitly accounts for permanent differences between market and non-market areas and common transitory shocks. I find that the introduction of market-based dispatch methods has reduced fossil-fuel production costs by upwards of 15%, and that a simple comparison based on the Olley-Pakes decomposition would overstate these gains.

Roughly half of electricity in the United States continues to be generated by plants called upon to operate by the local monopolist operating under cost-of-service regulation. Policymakers are therefore faced with the question of whether markets should be expanded or scaled-back. The answer depends on the balance between market failures and regulatory shortcomings. While market power is certainly a concern for market monitors, my results suggest that these concerns are far outweighed by the benefits realized by more efficient allocation of output though market-based dispatch.

Chapter 3

A Roy Model of Social Interactions

> "To show him the world before he knows men is not to form him but to corrupt him; not to instruct him but to deceive him." Rousseau (1979) [789]

3.1 Introduction

The influence of one's peers in shaping the educational environment has been a central concern throughout the history of educational discourse. Striking examples abound: Gans (1965) describes an insidious form of social interactions in which Italian immigrant communities in Boston's West End impose costs on individuals who "act mobile." Wilson (1987) provides qualitative evidence that the development of an "underclass" of black city dwellers on Chicago's South Side was due to the emigration of working families and the resulting decrease in role models and neighborhood quality.[1]

To better understand these phenomena, economists have developed models of social interactions by putting environmental variables, such as the mean behavior of one's social group or

[1] Many ethnographers describe similar phenomena around the globe: the Buraku Outcastes of Japan (De Vos and Wagatsuma (1966)); Blacks in America (Fordham and Ogbu (1986)), the Maori of New Zealand (Chapple, Jeffries, and Walker (1997)), Blacks on Chicago's south side circa 1930 (Drake and Cayton (1993)), the working class in Britain (Willis (1981)), among others.

the mean educational attainment in one's neighborhood, into agents' utility functions.[2,3] In this class of models, peers are a source of monotonic externalities; unruly peers cause more trouble and smarter peers encourage higher academic achievement (Becker and Stigler (1974), Becker (1996), Benabou (1993), Bernheim (1994), Akerlof (1997)). Becker and Murphy (2000) call this sort of complementarity between individual actions and those of one's peers "the fundamental assumption in analyzing the influence of social capital...on closely related behavior" (p.9)

Empirical evidence in favor of models which predict that an enhanced social environment leads to positive individual outcomes has been ambivalent.[4] While many authors confirm the hypothesis using data sets ranging from primary and secondary students in Texas to freshmen in the US Air Force Academy (Carrell, Fullerton, and West (2009); Hanushek, Kain, Markman, and Rivkin (2003); Hoxby (2000); Hoxby and Weingarth (2005); Duflo and Saez (2003); Duflo, Dupas, and Kremer (2008); Imberman, Kugler, and Sacerdote (2009); Goux and Maurin (2007), Hanushek, Kain, Markman, and Rivkin (2003); Hoxby (2000); Hoxby and Weingarth (2005)), others find no evidence of peer effects or occasional negative effects from increases in mean achievement or socioeconomics status of one's peer group (Sanbonmatsu, Kling, Duncan, and Brooks-Gunn (2006); Kang (2007); Angrist and Lang (2004); Carrell, Davis, Sacerdote, and West (2010)).

To reconcile the general consensus that peers *matter*, with the elusive nature of measuring exactly *how*, in this paper we take a primitive view of social interactions using insights from neoclassical economics. Modelling the endogneity of contacts within narrowly defined social settings we posit the existence of a 'market for peers' analogous to a traditional labor market. In the spirit of Becker (1965), agents derive utility from final goods produced by combining time and market inputs. Production of final goods, however, occurs in peer groups, which we cast as firms in a two sector Roy model (Roy (1951)). Our focus is on equilibria in which the effect of peers is

[2]Manski (1993) partitions the space of social interactions into three categories: endogenous effects, exogenous effects, and correlated effects. Endogenous effects occur when an individual's behavior is directly influenced by that of her peers. Exogenous (or contextual) effects occur when individual behavior is influenced by group composition or neighborhood characteristics. Correlated effects are present when individual and group behavior are related because peers share similar traits. We will not attempt to distinguish these important channels. In what follows, all of these categories interact to determine behavior through an equilibrium mechanism.

[3]Austen-Smith and Fryer (2005), Berman (2000), and Iannaccone (1992) are notable exceptions.

[4]See Durlauf (2004) for a careful review of the literature on peer effects in education, crime, welfare participation, and health.

mediated through an implicit price mechanism akin to Becker (1973); an agent's contribution to group production determines the share of output she receives.

With the emergence of distinct sectors within social markets, heterogeneity in ability leads individuals to select sectors based on comparative advantage. We characterize equilibria under two different assumptions: (i) industry production functions are concave in labor inputs, (ii) production functions are convex. Since the number of complexities to generalize the model is only bounded by one's ability to reinterpret variables from classical price theory, we limit the model to these basic characteristics. It would be relatively straightforward to extend the basic model to allow for many sectors and n-dimensional skill (Heckman and Scheinkman (1987)), as well as hierarchies and endogenous group size (Rosen (1982)), and apply the results from those papers to the study of social interactions through our approach.[5] It is important to emphasize at the outset that there are no intrinsic externalities built into the model. While we show the same basic results hold when the selection problem is introduced to a standard 'social multiplier' model in B.3, in the main text we focus attention on how endogenous sorting alone can also reconcile the conflicting empirical evidence aluded to above.

When comparative advantage is the guiding principle of peer group organization, the effect of moving a student to an environment with higher-achieving peers is an equilibrium sorting outcome. An individual's behavior depends on where in the new distribution she lands, and on the effective 'wages' that clear the social market. Put differently, selection into peer group roles is determined by the intersection of supply and demand for various skills; and peer effects are obtained through market prices. Thus, peer quality might be a source of linear or non-linear, positive, or even negative influences. If the demand function is approximately linear, for instance, the model predicts mean peer quality to exhibit positive and linear effects. Conversely, if production is subject to diminishing marginal returns, the model predicts estimates of peer effects to differ in size and magnitude depending on the location of the initial equilibrium, and the nature of the ability distribution. In this sense, the model can rationalize the widely varying

[5]Other possible extensions would allow individuals to invest in human capital (see Becker (1964); Ben-Porath (1967); Rosen (1972)), or to search for a peer group within and across sectors (Jovanovic (1979a,b); Miller (1984); Neal (1999)). To understand the implications of the sorting of individuals into groups when membership is costly and benefits depend monotonically on group composition see Cutler and Glaeser (1997).

results on peer effects found in the empirical literature without appealing to externalities.[6]

Moreover, our Roy model of social interactions has implications for the identification of peer effects. Since social wages and a student's comparative advantage are typically unobserved, key determinants of individual choice operate through the error term. Moreover, these unobservables may vary only on the school or neighborhood level and will, even under random assignment, be correlated with the regressor of interest (e.g., poverty rates, or the mean behavior of other students). Therefore, identification of neighborhood and peer effects may be more difficult than Manski (1993) describes—one not only has to solve the reflection problem and deal with the systematic sorting of individuals into social settings, but one must also account for the presence of group level unobservables that determine behavior. Even if individual behavior were to depend directly on the group mean, we show that if contacts within social markets are endogenous, then the parameters of interest are usually not identified.

Finally, we provide evidence consistent with our model's key prediction: Since similar individuals facing the same social wages have a common comparative advantage, all else equal, a student's propensity to act-out should be correlated with her ordinal rank in the ability distribution. Using two data sources, New York City Public Schools administrative records (NYCPS) and the National Educational Longitudinal Study (NELS), we demonstrate that, *ceteris paribus*, individuals' academic rank significantly affects the probability of exhibiting serious problem behaviors. In the NYCPS data, which contain information on the same students gathered at multiple points in time, we exploit transitions from elementary school (5th grade) to middle school (6th grade) to estimate that a fifty percentile decrease as opposed to a fifty percentile increase in rank among schoolmates (presumably from moving to a different school with more academically able peers) is associated with roughly a five percentage point increase in the probability of a serious behavioral incident (over a baseline of about 0.08). In doing so, we are able to control for student specific determinants of behavior, but not for systematic choice of school. To account for systematic sorting into schools, we use a student's hypothetical change in rank if they attended their zoned school (i.e. the default school based on their physical address) as an instrument for

[6]Additionally, there is the potential for multiple equilibria when social production exhibits increasing marginal returns to scale. While increasing marginal returns have formed the basis of a 'social multiplier' in settings with a single activity (Becker and Murphy (2000); Glaeser, Sacerdote, and Scheinkman (2003)), the selection problem induced by competing activities means that changes in peer ability may have ambigious effects on individual behavior.

actual change in rank based on the school they choose to attend. This approach supports our findings.

Our second dataset is the National Educational Longitudinal Study (NELS). NELS allows us to relate a student's behavior in different classrooms to a proxy for her course specific rank. We show that a fifty percentile decline in rank across subjects is associated with a ten percentage points higher probability that the teacher reports behavioral problems in the course for which she has the lower rank (over a baseline of about 0.40).

While these data are inconsistent with models that predict peer quality to exhibit positive monotonic externalities, we urge the reader to interpret our findings with two important caveats. First, as mentioned above, the estimates are not well identified peer effects. Second, models which predict negative peer externalities (e.g., smarter peers may decrease achievement) might also be consistent with our results.

The remainder of the paper is organized as follows. Section 3.2 develops our formal model, provides conditions that can explain the widely varying estimates found in the literature, and explores the implications of the comparative advantage approach for predicting the efficacy of social programs *ex ante*. Section 3.3 discusses identification of peer effects in the presence of comparative advantage, and shows evidence from two large data sets that is consistent with our model. Section 3.4 concludes. There are two appendices. Appendix B describes the data used in our analysis and how we construct our samples. Appendix B.3 shows how our approach is equivalent to a traditional social multiplier framework that allows for multiple social activities.

3.2 The Market for Peers

3.2.1 A Roy Model of Social Interactions

The economic model we propose in this section is a simplified version of the well-known multi-sector choice problem, and builds upon impressive literatures designed to understand the evolution of earnings, the (hedonic) pricing of skills, and the assignment of workers to firms (e.g., Ben-Porath (1967); Heckman and Scheinkman (1987); Heckman and Sedlacek (1985); Murphy (1986); Rosen (1974, 1982, 1983); Roy (1951); Sattinger (1979, 1993); Tinbergen (1956); Willis and Rosen (1979)). The novelty in our approach lies in the application of these classic methods to develop a theory of social interactions where contacts within a social market are endogenous and peer quality does not act as a direct externality. The paper most similar to ours is Heckman and Sedlacek (1985), who develop an equilibrium model of self-selection in the labor market. We extend Heckman and Sedlacek (1985) by considering the case of increasing returns to scale on the industry level, but we cannot implement their empirical exercise because we observe neither 'social wages' nor individuals' choices of sectors directly.

A. The Basic Building Blocks

Let there be a continuum of agents with unit mass. Every agent is endowed with one unit of (non-transferable) time. There are two activities in which agents can engage with their peers: studying or mischief. These activities are exclusive and undertaken by separate social groups in one of two sectors: 'nerds' and 'troublemakers'. Each sector, indexed by $j \in \{N, T\}$, combines the effective units of its members' time with another input we label 'capital' according to a general, twice continuously differentiable industry production function $F_j\left(L_j, K_j, A_j\right)$. Let A_j denote a technology shifter, such as school or neighborhood quality, or the quantity of policing. L_j represents the total supply of effective labor units to sector j, and K_j denotes the supply of effective capital. We allow capital to broadly represent any non-human input into groups' production (e.g., textbooks, sharp scissors, but also labor market conditions, or expectations thereof).

Agents are heterogenous along two dimensions. Their varying size and strength yield differences in the ability to cause trouble, whereas heterogeneity in cognitive ability implies differences in their ability to be a true nerd. Let the continuous function $\sigma_N(i) : [0,1] \to \mathbb{R}_+$ denote the effective units of 'nerdiness' that agent i is capable of contributing to the group (e.g., expertise in differential geometry). Analogously, agent i's troublemaking ability is given by $\sigma_T(i) : [0,1] \to \mathbb{R}_+$. We assume that agents are solely interested in maximizing their social income

$$U(i) = \max\left\{\sigma_N(i) w_N, \sigma_T(i)\, w_T\right\}, \tag{3.1}$$

where w_N and w_T are the market clearing wages for effective units of nerd and troublemaking labor, respectively. As in Heckman and Sedlacek (1985); Welch (1969); Heckman and Scheinkman (1987), earnings follow the linear in characteristics approach developed by Gorman (1980); Lancaster (1966). Note that there are no explicit peer externalities built into agent's utility. That is, given

w_N and w_T, the behavior of one's peers has no influence on own decisions. In section 3.2.4, we relax this assumption and allow for more general utility functions. Here, however, we show how sorting into peer groups alone can produce 'peer effects'.

Individuals maximize their social income by choosing either the nerd or troublemaking sector according to a simple cut-off rule (Roy (1951)). Let $\sigma(i) \equiv \frac{\sigma_N(i)}{\sigma_T(i)}$ denote agent i's skill as a nerd relative to that as a troublemaker, and order agents such that $\sigma'(i) \geq 0$. The agent indifferent between the two sectors, i^*, has a skill ratio of

$$\sigma(i^*) = \frac{w_T}{w_N}. \tag{3.2}$$

All individuals with index $i \geq i^*$ join forces with the nerds, and individuals with $i < i^*$ become troublemakers. In our price theory of social interactions, comparative (rather than absolute) advantage determines an individual's choice of sector.

By individual optimization and market clearing, labor supply to both sectors is given by:

$$L_N^* = \int_{i^*}^{1} \sigma_N(s)\, ds \tag{3.3}$$

$$L_T^* = \int_{0}^{i^*} \sigma_T(s)\, ds. \tag{3.4}$$

Equations (3.3) and (3.4) characterize the supply side in the market for peers. Equilibrium, however, also depends on the demand side, and therefore on the shape of the industry production functions. Below, we consider cases in which production is concave or convex in labor inputs.

B. Concavity in Labor Inputs

In the theory of the firm, it is typically assumed that labor exhibits diminishing returns to scale on the firm as well as the industry level. If, for instance, increasing the number of troublemakers does more to increase the probability of getting caught than of winning a fight, then the production function in the troublemaking sector will be concave in L_T.[7] In equilibrium, competition in the

[7] This holds for effective units, regardless of the number of participants. A brilliant student answering all of the questions or a talented athlete hogging the ball might be an example of many effective units concentrated in a single person diminishing the marginal social product for others.

market for peers ensures that nerd and troublemaking labor are paid their marginal products:

$$w_j = \frac{\partial}{\partial L} F_j \left(L_j^*, K_j, A_j \right). \tag{3.5}$$

With free entry into both the nerd and troublemaking sectors, individual peer groups earn zero profits. That is, all output is divided among group members.[8]

Substituting (3.5) into (3.2), market clearing yields the equilibrium condition

$$\delta\left(i^*\right) \equiv \frac{\frac{\partial}{\partial L} F_T(L_T(i^*), K_T, A_T)}{\frac{\partial}{\partial L} F_N(L_N\left(i^*\right), K_N, A_N)} = \sigma\left(i^*\right), \tag{3.6}$$

where $\delta\left(i\right) : [0, 1] \rightarrow \mathbb{R}_+$ denotes the ratio of marginal products in both sectors when the threshold index separating sectors is i. Since $\delta'\left(i\right) \leq 0$ for all i, the 'relative demand curve' in the market for peers is (weakly) downward sloping.[9] To see this, note that equations (3.3) and (3.4) respectively imply $\frac{dL_N}{di} < 0$ and $\frac{dL_T}{di} > 0$; and concavity of the industry production functions causes the ratio of marginal products to decrease as labor shifts from the nerd into the troublemaking sector. We can now describe equilibrium graphically.

Figure 3.1 shows equilibrium in the basic model when production in both sectors is concave in labor inputs. As described above, it features downward sloping demand and upward sloping supply. There is a unique equilibrium at i^* with market clearing relative prices, $\frac{w^T}{w^N}^*$, determined by the intersection of supply and demand. All individuals with $i < i^*$ select into the troublemaker sector and individuals with $i \geq i^*$ choose to be nerds.

Suppose there is a shift in troublemaking technology—less police surveillance or an increase in the availability of weapons—holding everything else constant. An increase in troublemaking technology is represented by an outward shift of the δ-schedule in Figure 3.1, which results in higher relative wages for troublemakers and fewer nerds. A decrease in troublemaking technology has the opposite effect: an inward shift of the δ-schedule, a decrease in the relative wages of troublemakers, and an increase in the number of agents who choose to become nerds.

[8] Assuming identical peer groups within sectors, the number of groups adjusts such that $f_j\left(l_j, k_j, a_j\right) = c_j$, where c_j is the fixed cost of operating in sector j, and lower case symbols denote the group level analog of their upper case counterparts.

[9] Technically a demand curve gives the quantity demanded at a particular price, all else equal. $\delta\left(i\right)$, however, denotes the marginal individual consistent with a certain wage ratio. Therefore, δ should more appropriately be thought of as a demand side equilibrium schedule.

Figure 3.1: *Equilibrium with Diminishing Marginal Product in Both Social Sectors*

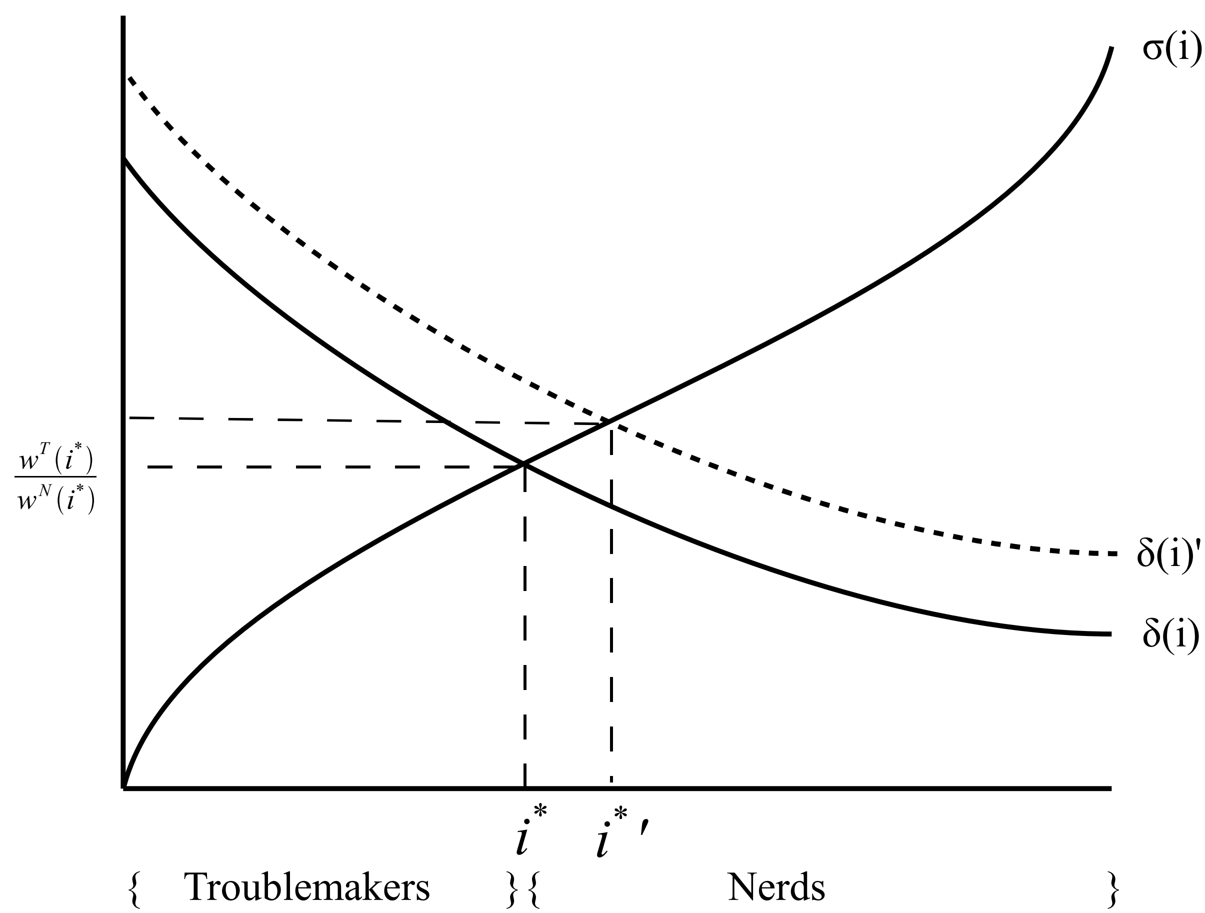
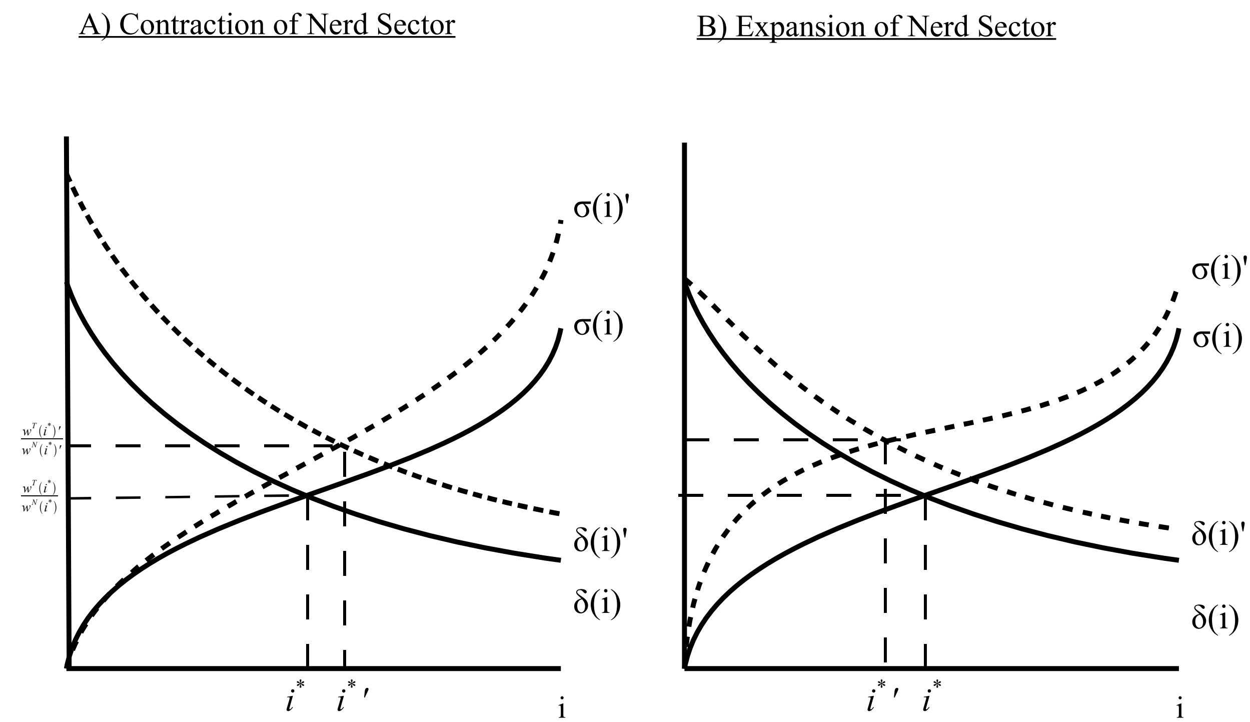


Figure 3.2: *The Effect of Higher Peer Quality when Marginal Product is Diminishing in Both Sectors*



Comparative statics with respect to the skill disribution, however, can be more counterintuitive. Consider, for instance, an increase in nerd skill among the population holding troublemaking skills fixed. First, an increase in agents' nerdiness shifts the supply curve inward (from $\sigma(i)$ to $\sigma(i)'$). Second, the demand curve shifts outwards (from $\delta\,(i)$ to $\delta\,(i)'$) due to the fact that with more academically able peers there will be more efficiency units of nerd skill supplied at any i. While both shifts lead to an unambigous rise in the relative wage of troublemakers, the effect on quantities in indeterminate.

Figure 3.2 illustrates the situation. In Panel A, the wage from being a nerd drops more rapidly with effective labor in the sector, leading to a larger outward shift of $\delta(i)'$, which is one factor contributing to the overall contraction in the nerd sector. The other contributing factor is that the increase in nerd skill comes disproportionately from the upper end of the distribution, so that the expansion in δ is larger at the upper end of the distribution[10], and the intersection of the two curves is therefore further to the right. In Panel B, social wages are less responsive to sector labor supply, and the increase in skill is more concentrated to the left of the initial equilibrium. While counterintuitive, an overall increase in the nerd skills actually yields an expansion in the size of the nerd sector.

C. Convexity in Labor Inputs

As discussed above, the assumption that the marginal utility of a social activity is increasing in overall participation has been the focus of much of the work on social interactions. Study groups allow students to benefit from division of labor on a lab project, and ensure individual students do not waste time stuck on a question to which someone else in the group knows the answer (Lazear (2001)). More troublemakers at a school can divert teachers' attention and thereby reduce others' probability of punishment (Dipasquale and Glaeser (1998)). We now consider the nature of equilibria when there are two social sectors characterized by such complementarities.

One way to reconcile increasing returns to scale on the industry level with the existence of many firms in a competitive market is the concept of *external increasing returns to scale* pioneered by Marshall (1890) and formalized by Ethier (1982b,a). The key idea is that individual firms are price takers and produce subject to diminishing marginal returns, but their activities exhibit positive externalities strong enough to cause marginal returns on the industry level to increase. Suppose, for instance, that the size of the market or the cost of production depend on the number of firms—say, because more firms invest in a new, more efficient technology—and that firms fail to internalize this spill-over effect. Then, production might exhibit increasing returns to scale at the industry level, but decreasing marginal returns at the firm level (Murphy, Shleifer, and Vishny (1989)). Another example of external economies, due to Marshall (1890), are advances in "trade-knowledge" which might be hard to keep secret from firms within the same industry.[11]

[10]Note that effective labor in the nerd sector is integrated on $[i^*, 1]$, so that the shift in δ will be larger for any i^* the more concentrated a given increase in the distribution of σ_N is in the upper end of the distribution.

[11]Starting with Arrow (1962); Ethier (1982b), externalities have often been used to model equilibria in which firms compete against each other in the presence of increasing returns to scale. Romer (1986, 1987); Lucas (1988); Prescott and Boyd (1987), for instance, demonstrate the importance of knowledge accumulation and specialization for economic

In the market for peers we assume that production is concave on the peer group level, but convex on that of the industry. The activities of one large troublemaker group might be harder to coordinate than those of a smaller one leading to a higher risk of getting caught for any individual member. However, more troublemakers at a school can divert teachers' attention and thereby reduce others' probability of punishment. Yet, the inability to coordinate efficiently precludes individual groups from becoming too large and reaping the full benefits of increasing returns to scale at the industry level.[12] Therefore, there exist multiple independent peer groups within a sector, each of which takes the size of the industry as well as the prevailing wages as given.

Assuming that the industry production function is convex in labor adds one additional wrinkle. Since peer groups do not take the positive externalities of their hiring decisions into account, the marginal product of labor is smaller on the group than on the industry level. Thus, in equilibrium, wages cannot equal the marginal product of labor for the whole industry. Instead, under free entry into the market for peers, a zero-profit condition determines equilibrium wages. As in the case of concave production, we assume that all industry output goes to the agents in the particular sector.[13]

Let profits in sector j be given by

$$\pi_j = F_j\left(L_j, K_j, A_j\right) - w_j L_j. \tag{3.7}$$

Assuming $F_j\left(0, K_j, A_j\right) = 0$ for all K_j and A_j, equation (3.7) directly implies a wage per efficiency unit equal to

$$w_j = \frac{\int_0^{L_j} \frac{\partial}{\partial L} F_j\left(s, K_j, A_j\right) ds}{L_j} \equiv \overline{\frac{\partial}{\partial L} F_j\left(L_j, K_j, A_j\right)}$$

---

growth. Murphy, Shleifer, and Vishny (1989) argue that increasing retruns in the form of aggregate demand spill-overs might explain why some countries appear to be stuck in a unindustrialized equilibrium. Krugman (1991) shows how increasing returns to scale shape economic geography. In the literature on international trade external increasing returns to scale have, for instance, been used to explain the pattern of trade between developed countries (see Helpman (1984); Krugman (1991) reviews). For a model of trade in which returns to scale are internal to firms see Krugman (1979).

[12] See Becker and Murphy (1992) on the trade-off between returns to scale due to specialization and coordination costs.

[13] The following derivations do not depend on the absence of profits in equilibrium. An alternative assumption leaving our conclusions essentially unaffected would be that labor is compensated with a fixed share of revenues.

where $\overline{\frac{\partial}{\partial L_j} F_j\left(L_j, K_j, A_j\right)}$ denotes the the average marginal product of labor on the industry level.[14]

Market clearing implies

$$\sigma\left(i^*\right)=\frac{w_T}{w_N}=\frac{\overline{\frac{\partial}{\partial L} F_T(L_T(i^*), K_T, A_T)}}{\overline{\frac{\partial}{\partial L} F_N\left(L_N\left(i^*\right), K_N, A_N\right)}} \equiv \delta\left(i^*\right).$$

Note that $\delta^{'}(i) \geq 0$ for all i. In words, the convexity assumption implies that the ratio of marginal products increases as labor flows from the nerd to the troublemaking sector. Thus, under increasing returns to scale in labor, the 'relative demand' schedule is upward sloping.

The existence of relative supply and demand curves that are both upwards-sloping creates the potential for multiple equilibria as follows.

Proposition 1. *There exist at least two equilibria with a positive mass of both nerds and troublemakers if:*

$$(i)\ \delta(0)>\sigma(0), \delta(1)>\sigma(1),\ \textit{and}\ \delta(i)<\sigma(i)\ \textit{for any}\ i \in(0,1),$$

or if

$$(ii)\ \delta(0)<\sigma(0), \delta(1)<\sigma(1), \textit{and}\ \delta(i)>\sigma(i)\ \textit{for any}\ i \in(0,1).$$

There exists at least one equilibrium with a positive mass of both nerds and troublemakers, and another one in which all agents become either nerds or troublemakers if

$$(iii)\ \delta(1)>\sigma(1)\ \textit{and}\ \delta(i)<\sigma(i)\ \textit{for any}\ i \in(0,1),$$

or if

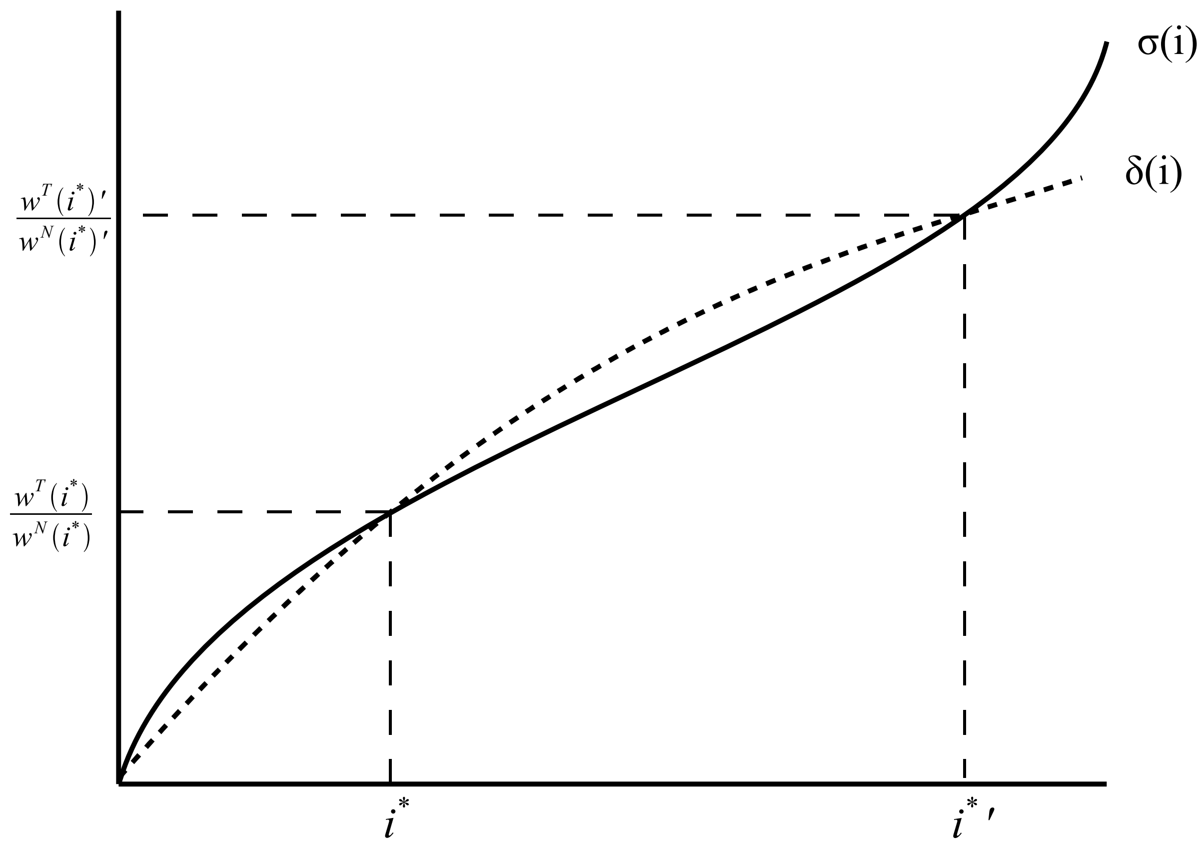
$$(iv)\ \delta(0)<\sigma(0)\ \textit{and}\ \delta(i)>\sigma(i)\ \textit{for any}\ i \in(0,1).$$

Proof. By continuity of δ and σ the proof follows immediately from the Intermediate Value Theorem and by recognizing that if $\delta(1) \geq \sigma(1)$ or $\delta(0) \leq \sigma(0)$ a corner solution may obtain. □

Figure 3.3 depicts a scenario in which increasing marginal product yields multiple equlibria—at the origin, i^*, and $i^{*\prime}$. Only equilibria in which the 'demand curve' intersects the 'supply curve' from above are locally stable. To see this, consider the adjustment process following a small

[14]Since firms within a sector take wages as given and compete for labor, wages are also equal to the marginal product of labor on the firm level. In equilibrium the number of firms must adjust such that each of them earns zero profits.

Figure 3.3: *Multiple Equilibria when Marginal Product is Increasing in Sector Labor Supply*



shock to wages. From the initial equilibrium at i^*, a small decrease in relative wages (along the δ-schedule) will lead to labor flowing out of the troublemaking and into the nerd sector, which will cause relative wages to decline further and lead to even more agents switching sectors. The process continues until the market reaches a new equilibrium at the origin. Conversely, a small increase in wages (along the δ-schedule) will lead to labor flowing into the troublemaking sector. This causes relative wages to increase even more, thereby inducing more nerds to become troublemakers until the market reaches equilibrium at $i^{*\prime}$. Similar reasoning shows that the equilibrium at $i^{*\prime}$ is stable. Given the existence of multiple equilibria, our model may rationalize starkly different behaviors of agents in observationally similar markets.[15]

The case of convex production is closely related to models of a 'social multiplier' (Becker and Murphy (2000); Glaeser, Sacerdote, and Scheinkman (2003)). In these models, social spillover effects arise because an individual's marginal utility from taking a particular action is assumed to increase in the number of agents in her reference group who behave in the same way. In our model, an agent's productivity increases as others join the same sector, which raises her wage and thereby the net utility gain from choosing this sector. In symbols:

$$\frac{d}{dL_j}\left(w_j\sigma_j\left(i\right)-w_{j'}\sigma_{j'}\left(i\right)\right)=$$
$$\left[\frac{\partial}{\partial L_j}\left(\overline{\frac{\partial}{\partial L_j}F_j\left(L_j,K_j,A_j\right)}\right)\sigma_j\left(i\right)-\frac{\partial}{\partial L_{j'}}\left(\overline{\frac{\partial}{\partial L_{j'}}F_{j'}\left(L_{j'},K_{j'},A_{j'}\right)}\right)\frac{dL_{j'}}{dL_j}\sigma_{j'}\left(i\right)\right]>0$$

for $j\neq j'$. That is, the net utility from choosing sector j over j' increases in the amount of labor employed in j. Our theory could thus be interpreted as providing alternative micro-foundations for the assumption of increasing marginal utility[16]. Here, however, the ability to sort into social sectors has the potential to obfuscate the complementarity between individual and group behavior.

3.2.2 Reinterpreting the Peer Effects Literature Through the Lens of a Roy Model

There is a large literature on peer effects in schools, neighborhoods, and other venues in which individuals interact. Surprisingly, research designs which exploit experimental and quasi-experimental

[15]When the marginal product for one social sector is increasing while the other is decreasing, the relative demand schedule may alternate between sloping upwards and downwards.

[16]In B.3 we show our core results hold when introducing a second social activity to a general social multiplier model.

variation often point in conflicting directions with comparable samples. In this section we show that our Roy model of social interactions is flexible enough to reconcile the seemingly disparate evidence. Put differently, we show that a model in which 'peer effects' are due to the systematic sorting of individuals *within* social markets can produce the disparate empirical patterns that have emerged in spite of (quasi) random assignment *to* social markets. In our stylized setting, when we use the term 'peer effects', we are referring to the change in individuals' association with troublemakers or nerds. In order to discuss their measured academic perfomance it is helpful to think of the troublemakers as spending substanially less social time studying.

We divide the empirical literature on peer effects into four mutually exclusive categories: analyses that report no significant peer effects, effects which are homogenous and positive (i.e. smarter peers increase achievement for everyone to the same extent), effects that are heterogeneous across the skill distribution, but nonetheless still positive, and analyses that find negative peer effects.

In what follows we assume that production functions are concave in labor inputs and provide sufficient conditions for our model to reconcile the findings of various studies.[17] We do not attempt to explain every nuance in the empirical literature on peer effects. For sure, there exist several competing models all of which can explain some aspect in isolation. Our goal is to show how our Roy model can reconcile broad but seemingly disparate findings in a parsimonious fashion.

A. No Peer Effects

One strand of the literature finds evidence of negligible peer effects (Angrist and Lang (2004); Cullen, Jacob, and Levitt (2005); Evans, Oates, and Schwab (1992); Lefgren (2004); Lyle (2007); Stinebrickner and Stinebrickner (2006)). Angrist and Lang (2004) evaluate Boston's Metco program, which buses minority students from high poverty neighborhoods in Boston to wealthier suburban schools. Their results indicate that, although the new Metco students are on average lower achieving, the change in peer group induced by these students does not affect test scores of elementary and middle school students in the suburban schools. Cullen, Jacob, and Levitt (2005)

[17] Conducting a similar analysis for the case of convex production functions yields more 'degrees of freedom' due to the potential for multiple equilibria.

analyze roughly fifteen thousand students who applied to nineteen schools through the Chicago Public Schools choice program. Using data from lotteries, their results imply that the academic impact of attending a new school with higher-performing peers is negligible.

Using solely the lens and language of our model, this implies that the marginal student, i^*, in these settings remains the same notwithstanding a change in peer group composition. Hence, the choice of sector for all other individuals does not change as well. To see why this might be the case in practice, consider Boston's Metco program (Angrist and Lang (2004)). A potential explanation for the lack of peer effects in this study is that Metco students are few relative to non-Metco ones and of lower academic ability. Despite the fact that average ability declines and both the 'supply' and 'demand' curves shift downward, the impact of Metco students on relative wages is likely small. As the relative ability of their non-Metco peers remains the same, our model predicts that almost none of them change sectors, leading to negligible peer effects.

Figure 3.4 illustrates this point. Imagine an increase in the number of Metco students, which shifts the supply curve downward from σ to σ', and the demand side equilibrium schedule from δ inward to δ'. Notice, large shifts only occur to the left of the initial equilibrium. More generally, note that a downward shift in the σ curve induces an inward shift of the δ curve, that while unambiguously lowering the relative wage for troublemaking, may leave the marginal i^* unchanged.

B. Homogeneous Positive Effects

Another portion of the peer effects literature finds that individual achievement increases at a constant rate with respect to mean peer quality. Hanushek, Kain, Markman, and Rivkin (2003) show, in a large matched panel data set of third through sixth graders in Texas public schools, that a one standard deviation increase in mean peer test score results in a .20 standard deviation increase in own test scores. Hoxby (2000) uses year to year variation in class-level gender and race composition; finding effects that range from .15 to .40 points for every one point increase in the class mean reading score.[18]

Through the lens of our model, this implies that a constant fraction of individuals shift sectors

[18] Other contributions in this vein include Boozer and Caciola (2001), Gaviria and Raphael (2001), Kang (2007), and Goux and Maurin (2007).

Figure 3.4: *METCO: The Effect of Lowering Academic Quality at the Bottom of the Distribution.*

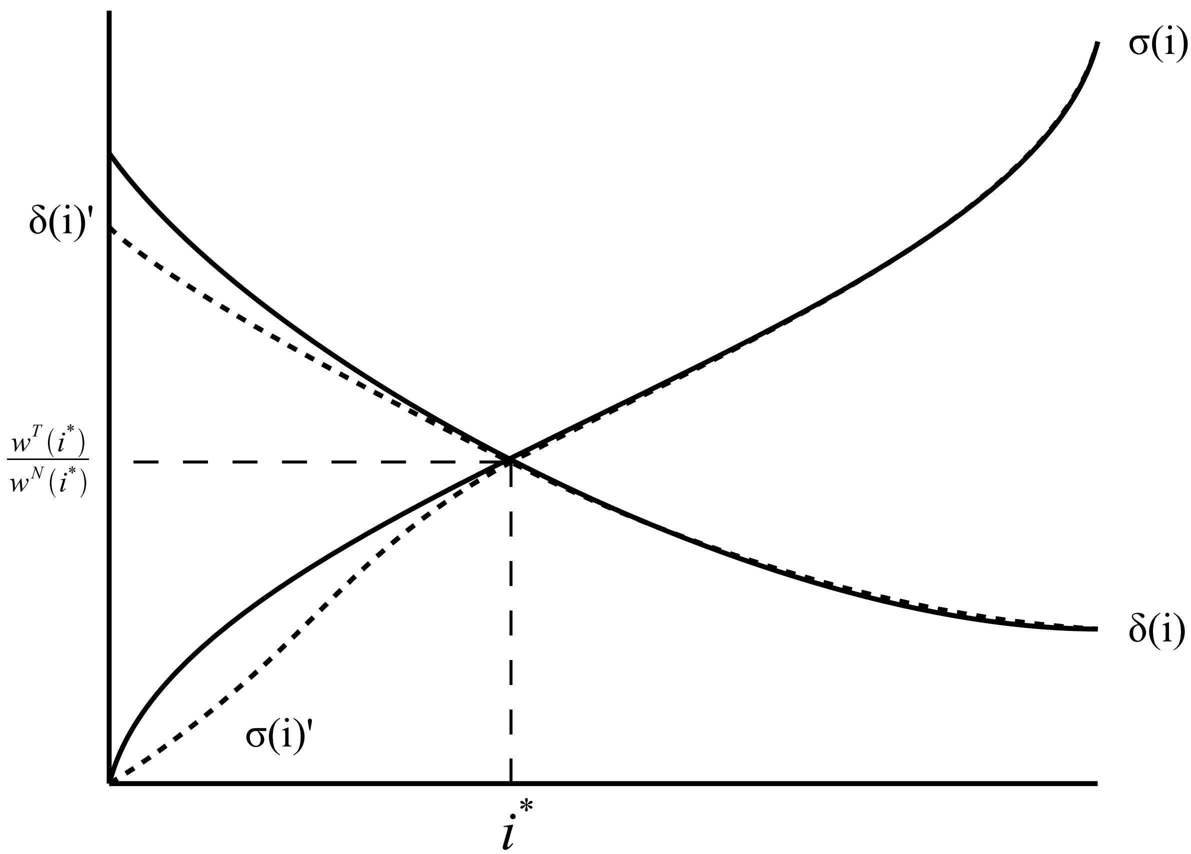
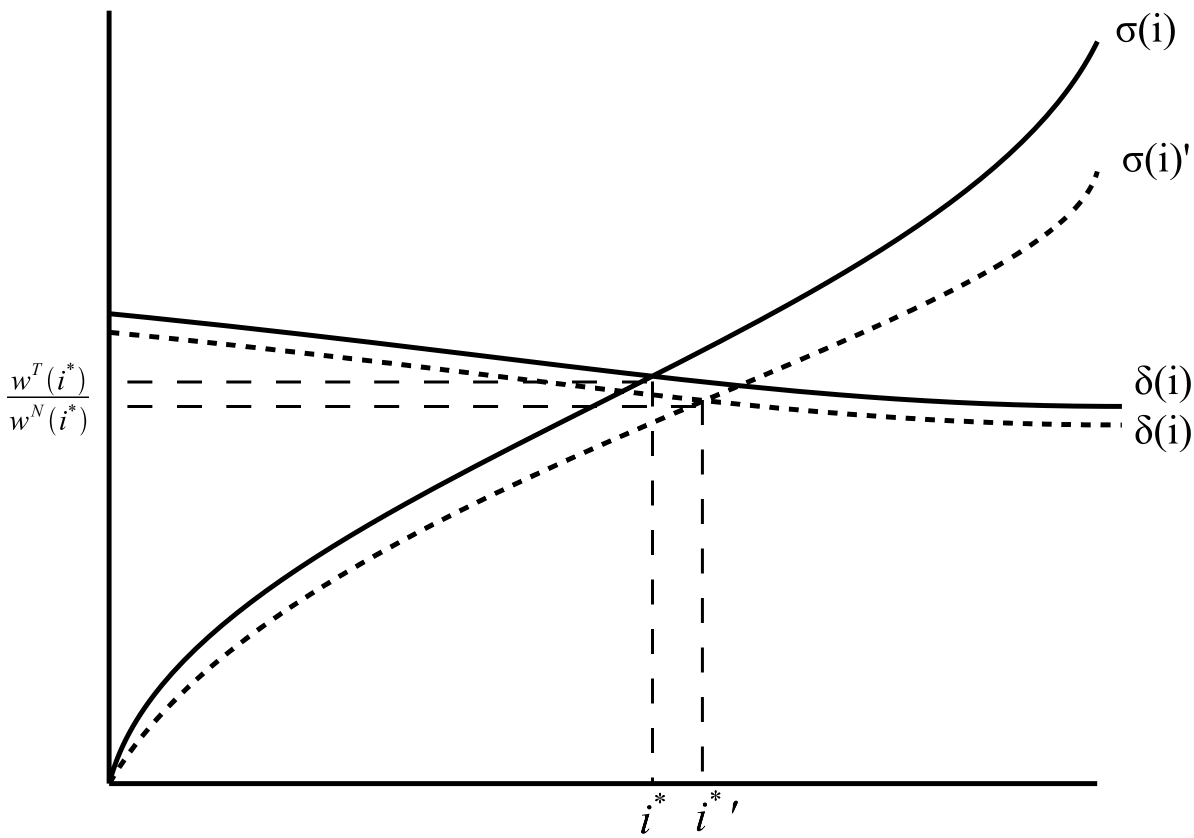


Figure 3.5: *Constant and Positive Effect of Average Ability on Sector Membership*



for every one unit increase in peers' mean test score. Figure 3.5 shows an example in which peer effects would operate linearly. In this example, the supply schedule (i.e. the distribution of relative ability) shifts almost parallel close to the initial equilibrium. Furthermore, the demand curve has constant negative slope around the initial equilibrium and is relatively unresponsive to shifts labor supply. Therefore, changes in peer ability lead to relatively small changes in relative wages, and a constant fraction of individuals switch sectors—resulting in constant linear peer effects.[19]

An explanation along these lines may partially explain the results of Hoxby (2000). As Hoxby (2000) identifies peer effects through plausibly random variation in gender and race composition in classrooms, it may be reasonable to assume that, over the relevant range, the ability distribution shifts one-to-one with its mean. Moreover, given the limited variation in cohorts' gender and racial composition, the demand schedule might be approximately linear in a neighborhood around the initial equilibrium.

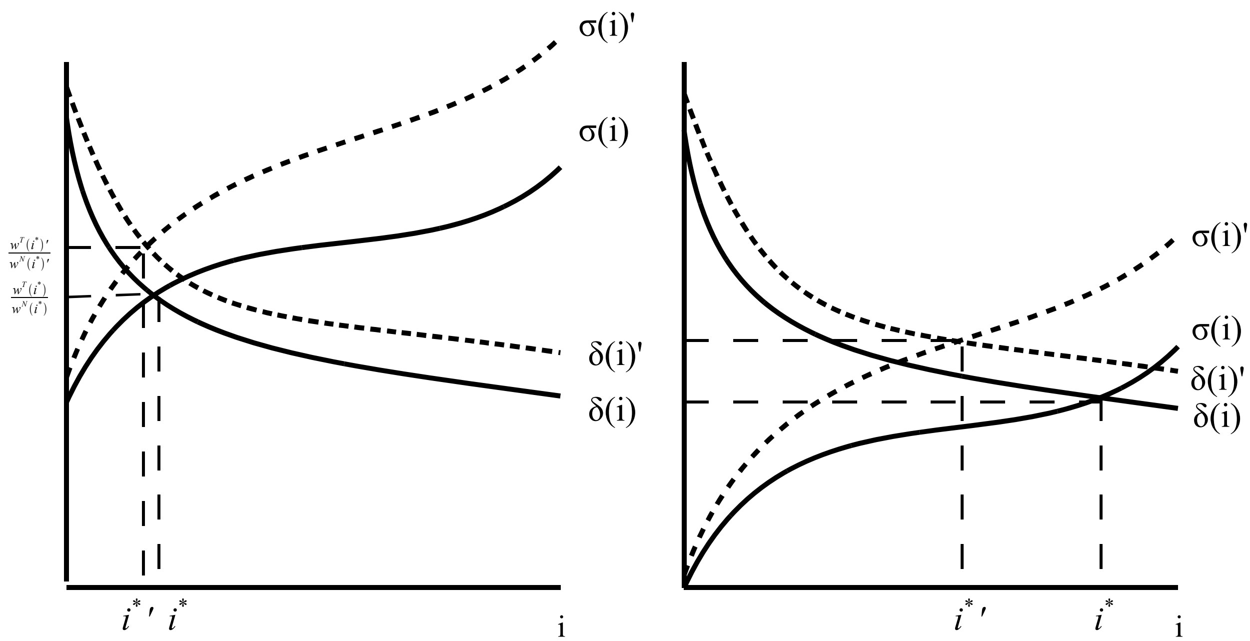
C. Heterogeneous Positive Peer Effects

A third category of the literature describes positive, but non-linear peer effects. Hoxby and Weingarth (2005), for instance, exploit a desegregation program in Wake County, NC, which produces exogenous changes in classroom peer groups. They find that based on a linear-in-means model a student's test score is expected to increase .25 standard deviations given a 1 standard deviation increase in peers' mean score. However, when they allow their results to differ depending on the decile of peer performance, they find that students benefit more from peers with an achievement level similar to theirs. For example, students in the bottom decile benefit most from the addition of students in the second and third deciles (a 10% increase in peers at the 15th percentile increases their performance by .19 standard deviations more than an additional 10% of students in the 8th decile).

Carrell, Fullerton, and West (2009) investigate peer effects among freshmen at the Air Force Academy who are randomly assigned to squadrons. They show that a one standard deviation increase in peers' average verbal SAT score results in a .565 standard deviation increase in freshman fall GPA for students in the bottom third of the expected achievement distribution compared to .361 and .312 for those in the middle and top third.

[19] We emphasize that the conditions we provide in the text are sufficient, but in no way necessary.

Figure 3.6: *Reconciling Heterogeneous Treatment Effects with the Comparative Advantage Approach*



Using Census data, Crane (1991) shows that the fraction of high-status workers in a neighborhood is negatively related to the likelihood of teen pregnancy and dropping out of school. These effects are much stronger in areas with the lowest levels of high-status workers.[20]

Figure 3.6 considers a scenario consistent with the results of Crane (1991) under the auspices of our model. The left panel depicts the situation in a neighborhood with a large number of high achievers (e.g., nerds in the language of the previous section). An increase in the presence of highly skilled individuals (shifting σ to σ') marginally decreases i^*. The right panel features an identical inward shift of the supply curve, but a substantially larger increase in the nerd sector.

[20]Similar non-linear peer effects are found in Burke and Sass (2008), Cooley (2010), Ding and Lehrer (2007), Duflo et al. (2008), Figlio (2007), Imberman et al. (2009), Zimmer and Toma (2000), and Zimmerman (2003).

The heterogenous effects for a given change in supply are due to the confluence of a concave relative demand curve, so that demand is more 'elastic' in Panel B, and that the initial size of the nerd sector is smaller. Thus the shift in relative supply is actually larger in the neighborhood of the marginal i^*. Taken together, these structural differences in market for peers yields markedly different behavioral responses to an identical change in skill composition.

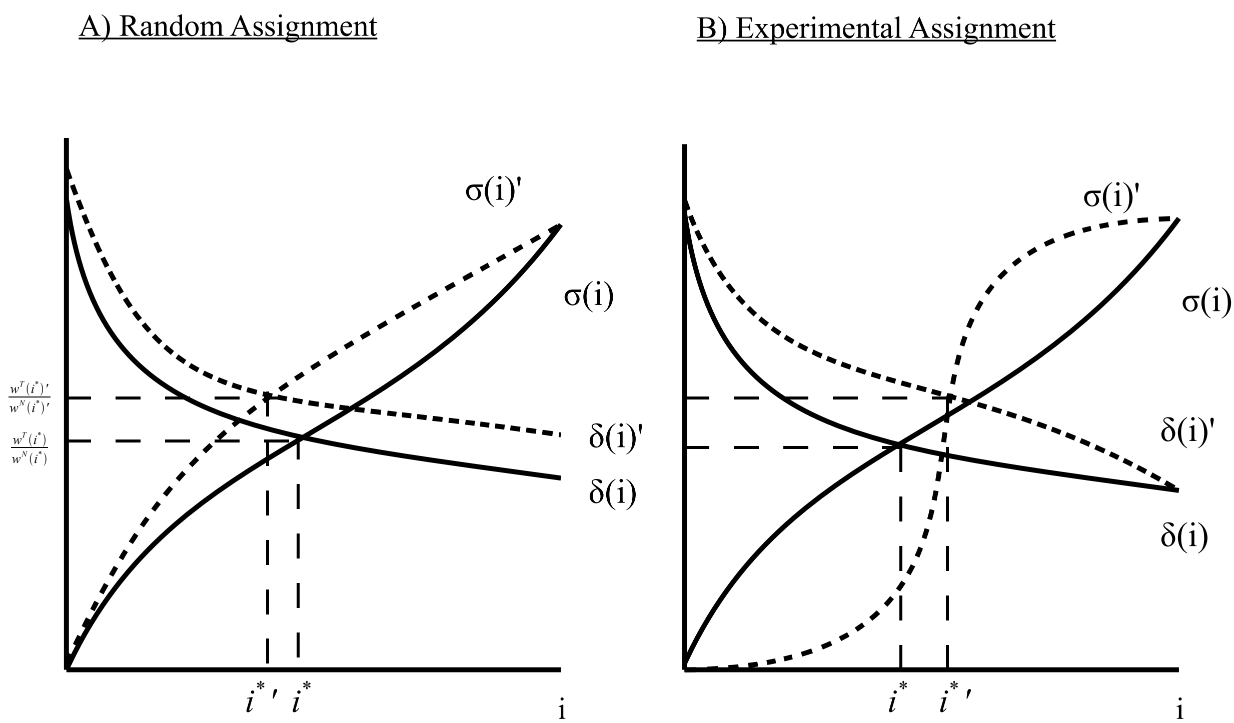
D. Heterogeneous, Negative Peer Effects

In stark contrast to the previously mentioned studies, a nascent literature provides credible evidence of incidents in which achievement declines in peer quality. Lavy, Silva, and Weinhardt (2009) use a sample of over a million students taking British age-14 tests to examine peer effects in English high schools. Exploiting the fact that students in their sample enter high school, and thus encounter a peer group that is 87% new on average, they demonstrate that peer effects are different for boys and girls. Girls are positively affected by peers in the top 5% (.07 standard deviation for a 10% increase) while boys are negatively affected (-.05 standard deviations). For boys, the negative effects are strongest among those at the top of the achievement distribution.

Based on the non-linear results in Carrell, Fullerton, and West (2009); Carrell, Davis, Sacerdote, and West (2010) implemented an experiment at the US Air Force Academy aimed at increasing the GPA of incoming freshmen who were predicted to score in the bottom tercile of the achievement distribution. To achieve this goal, squadrons in the treatment group were negatively sorted, while the composition of those in the control group continued to be random. Yet, the experiment did not have the intended effect: students in the treatment group projected to score in the bottom tercile of the distribution (the students the experiment was designed to help) experienced a .05 point *decline* in GPA compared to their counterparts in the control group. At the same time, the students in the bottom tercile who were randomly assigned to squadrons in the control group continued to experience GPA gains in squadrons with a higher fraction of academically talented cadets.

One possible explanation for these perplexing results is illustrated in Figure 3.7. In Panel A, we consider a candidate relative supply distribution σ' when a squadron has a high fraction of high achieving cadets due to random assignment. Compared to the marginal distribution of the cohort in bold lines, the higher fraction of cadets with high scores is due random assignment comes from

Figure 3.7: *Reconciling Results from Carrell et al. (2010) with the Comparative Advantage Approach*

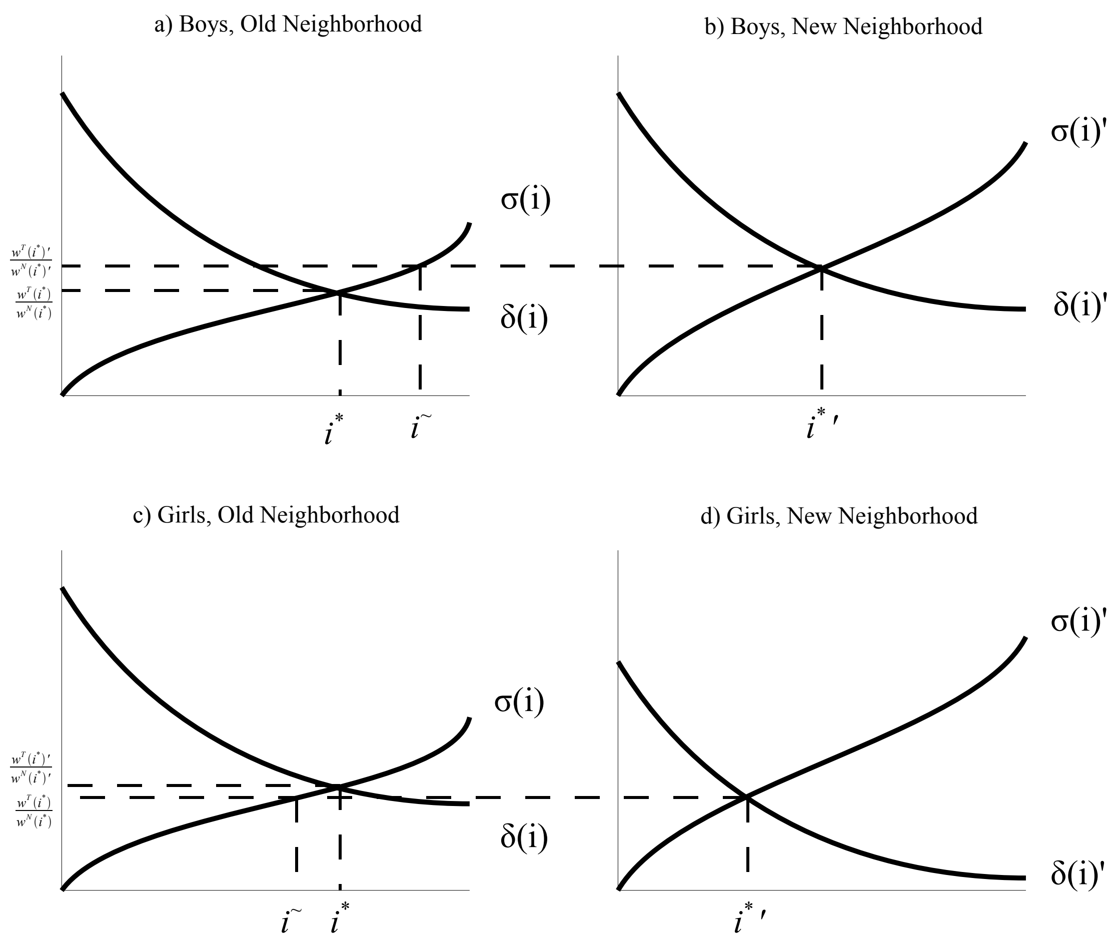


a reduction in the fraction of students from both the middle *and bottom* of the distribution. The resulting equilibrium consists of a higher fraction of nerds in the squadron. The scores of those at the bottom of the distribution improves due to either some actually associating with nerds, or due to the fact that that their fellow troublemakers are more academically inclined. When squadrons are arranged according to negative sorting, on the other hand, there is an increase in the fraction of students from *both* the top and bottom tercile, as the distribution becomes S-shaped when the middle tercile is removed. This mean-preserving spread of the distribution has relative demands at the boundaries equal to the marginal distribution, but is much flatter in the interior. Instead of exposing the more academically disadvantaged peers to talented study partners, the intra-squadron social dynamics result in greater isolation from them.

Another striking example of peer effects in this category comes from the Moving to Opportunity (MTO) experiment which provided housing vouchers for families in high poverty neighborhoods in Baltimore, Chicago, Los Angeles, and New York City to relocate to lower poverty neighborhoods (Kling, Ludwig, and Katz (2005); Katz, Kling, and Liebman (2007)). Evaluations of MTO show that female youth were affected positively by living in an ostensibly better neighborhood. Relative to the control group, female youth are 6.9% less likely to have ever had anxiety symptoms, are 9.1% less likely to have consumed alcohol during the past month, and have .08 fewer lifetime arrests for violent crimes. In contrast, male youth are affected negatively. Relative to the control group, male youth are 8.7% more likely to have had serious nonsports accidents, are 10.3% more likely to have smoked during the past month, and have .15 more lifetime arrests for property crimes.

Our model would predict the findings in MTO if *relative* wages increased (compared to the old neighborhood) for boys, but decreased for girls. Figure 3.8 depicts shifts of the supply and demand curves which could produce such a result. The top two panels refer to boys and the bottom two to girls. The panels on the left illustrate the conditions in the pre-treatment neighborhood and the panels on the right demonstrate an equilibrium in the treatment neighborhood. The set of students who switch sectors is bounded by i^*, the marginal individual in the old neighborhood, and by $\widetilde{i}$, the counterfactual marginal individual given the relative wages in the new environment. In moving to the new neighborhood there are two opposing effects on the relative demand schedule. The nerdier population tends to shift the δ-schedule outwards, while at the same time greater educational resources and supervision in the new neighborhood increase the relative returns to studying,

Figure 3.8: *Reconciling Results from Moving To Opportunity with the Comparative Advantage Approach*



which would shift the δ-schedule inwards. In contrast to models that predict a positive influence from the new environment, here the direction of the treatment effect is determined by the net effect on social wages.

In Figure 3.8 the inward shift in supply by going from one environment to the other is the same for boys and girls. That is, boys and girls in the experimental group face the same set of smarter peers after they move. If, however, the relative demand curve for girls shifts sufficiently far inward to overcome the outward shift in relative supply, then relative equilibrium wages move in opposite directions. A smaller shift in the demand curve for boys could be caused by multiple factors. If the nerd production function for girls is less concave with respect to labor, they will be less likely to be competed out of the group in an environment with greater effective supply. Conversely, if the troublemaking production function for boys is more concave with respect to labor, the very force that kept them from making trouble in their old neighborhood will raise the relative return to doing so in the new neighborhood where such skills are scarce. Alternatively (not depicted in the figure), it could have been the case that for boys the ability distributions between the old and new neighborhood differ sufficiently much for the supply shift to dominate, whereas for girls the inward demand shift might outweigh the change in relative supply.

3.2.3 Predicting the Efficacy of Social Interventions in the Presence of Comparative Advantage

The fundamental problem our model highlights is that the treatment effect of a social environment is an endogenous process that is determined *after* any potentially random assignment to a neighborhood, classroom, etc. Without observing social wages *ex ante*, there is no sure way of determining which of the conditions outlined above will hold before a program commences. Ultimately, an intervention's effect depends on production technologies, group specific capital, skill distributions, and the resulting market clearing prices, all of which are generally unobserved. Thus, it may seem that our theory has no *ex ante* predictions. This is only partially correct. Our model suggests a heuristic that can potentially help policy makers predict outcomes of small scale interventions that do not change equilibrium prices.

Using the lens of comparative advantage, if a policy maker is interested in predicting the behavior of a child after moving to a new neighborhood, a new school, or new classroom, then the relevant statistic is the behavior of children with the same characteristics in the new environment. The reason is simple: children with similar characteristics will likely have a common comparative advantage and can be expected to behave similarly when facing the same social wages.

The challenge is to find a way to compare agents across markets. Let Θ_j denote the set of individual characteristics which determine sectoral choice with intervention j. In a school intervention this may include, for example, test scores or a disciplinary record; in a neighborhood intervention height, weight, and motivation may be relevant characteristics. If one can identify Θ_j before an intervention commences, then students can be matched across social markets and the heuristic is straightforward.

Consider a few thought experiments. If Θ_j is test scores, then one can compare individuals across cities based on their prior scores. If Θ_j is 'innate ability', methods developed in Hansen, Heckman, and Mullen (2004) to extract measures of ability can be used to match individuals with the same ability across markets. If Θ_j involves non-cognitive skills such as those psychologists often refer to as "The Big Five"—Openness, Conscientiousness, Extraversion, Agreeableness, and Emotional Stability (e.g., Digman (1990))—one can develop pre-intervention surveys along these dimensions and match students on these five measures. Difficulties, however, arise when we have no theory or empirical evidence to inform Θ_j. In this case, one might use administrative or survey data to match on as many variables as possible, recognizing that the prediction will have more noise.

Assuming Θ_j is in hand, and that we can calculate a measure of relative skill, $\sigma(i)$, the prediction from our heuristic is directly related to traditional program evaluations. Let $Y(i)$ be an indicator variable equal to one if individual i chooses to be a nerd (and zero otherwise) in the old environment, and let $Y(i)'$ denote i's choice in the new environment. Then the average treatment effect from manipulating the environment for all i is equal to

$$ATE = \mathbb{E}\left[Y(i)' - Y(i)\right] = i^* - i^{*\prime},$$

where i^* and $i^{*\prime}$ denote the marginal individual in the old and new environment, respectively. In words, the average treatment effect is simply the fraction of individuals who switch sectors.

Interpreting our model more loosely, one could also think of outcomes (Y_0, Y_1) which are different from an agent's actual choice of sector, but nevertheless depend on it. For instance, let $Y_1(i|\Xi)$ denote i's test score (conditional on environmental variables Ξ) if i chooses to be a nerd, whereas $Y_0(i|\Xi)$ is her potential outcome as a troublemaker. In this case, the average treatment effect from transplanting a population of unit mass into a new environment characterized by Ξ' is

$$\begin{aligned}
ATE = &\int_0^{\min\{i^*(\Xi),i^*(\Xi')\}} \left(Y_0\left(s|\Xi'\right) - Y_0\left(s|\Xi\right)\right) ds \\
&+ 1_{\{i^*(\Xi)<i^*(\Xi')\}} \int_{i^*(\Xi)}^{i^*(\Xi')} \left(Y_0\left(s|\Xi'\right) - Y_1\left(s|\Xi\right)\right) ds + 1_{\{i^*(\Xi)>i^*(\Xi')\}} \int_{i^*(\Xi')}^{i^*(\Xi)} \left(Y_1\left(s|\Xi'\right) - Y_0\left(s|\Xi\right)\right) ds \\
&+ \int_{\max\{i^*(\Xi),i^*(\Xi')\}}^{1} \left(Y_1\left(i|\Xi'\right) - Y_1\left(i|\Xi\right)\right) ds,
\end{aligned}$$

where $i^*(\cdot)$ denotes the marginal individual in a given environment, and $1_{\{\cdot\}}$ is an indicator function equal to one if the condition in braces is satisfied. The first and last row in the equation above give the change in test scores for those individuals who do not switch sectors, whereas the middle row denotes the change in the outcome for those agents who do switch sectors (e.g., for nerds who become troublemakers or vice versa). Even if changing the environment from Ξ to Ξ' is beneficial in the sense that it raises both Y_0 and Y_1 for every individual, the average treatment effect could still be negative if the difference between Y_0 and Y_1 (conditional on the environment) is sufficiently large compared to the effect of environmental variables.

3.2.4 An Extension to the Basic Model

In this subsection, we outline an extension to the basic model presented above that recognizes the tradeoff that may exist between social activities and the ancillary costs or benefits of associating with a social group. In particular, students may value good grades for their own sake, or for the higher future standard of living that accompanies graduation. This raises the opportunity cost of associating with troublemakers, and encourages association with nerds even in the presence of low social wages.

To fix ideas, one can think of θ_j as the utility-scaled effect that association with sector $j \in \{N, T\}$ has on educational achievement or expected future income. To make the analysis tractable, we assume linearity as well as additive separability in the utility derived from social income and that incurred from θ_j. More specifically, agent i's utility is given by

$$U(i) = \max_{j \in \{N,T\}} \{w_j \sigma_j(i) + \theta_j\}. \tag{3.8}$$

It follows straightforwardly that agent i will choose to become a troublemaker if and only if

$$w_T \sigma_T(i) - w_N \sigma_N(i) \geq \theta_N - \theta_T.$$

In words, for i to join forces with the troublemakers it must be the case that the psychic benefit from joining, $(w_T \sigma_T(i) - w_N \sigma_N(i))$, outweighs the utility loss due to lower achievement, $(\theta_N - \theta_T)$.[21]

More generally, however, equilibrium is determined by the condition:

$$w_T(i^*) \sigma_T(i^*) - w_N(i^*) \sigma_N(i^*) = \theta_N - \theta_T, \tag{3.9}$$

where $w_j(i^*)$ denotes the equilibrium wage in sector j. From our basic model we know that, given social wages, the net psychic benefit from being a troublemaker, i.e. the left hand side of equation (3.9), is decreasing in an individual's index, whereas the right handside is constant from individual agents' point of view. Hence, as before, individuals with index $i \leq i^*$ become troublemakers, and those for whom $i > i^*$ choose the nerd sector. That is, equilibrium labor supply continues to be given by equations (3.3) and (3.4), and equilibrium wages will be determined as described above.

If we think of $\theta_N - \theta_T$ as the discounted net difference in future wages due to school-age social associations, it makes sense discount factor and educational attainment would be positively correlated.

3.3 Empirical Implications

3.3.1 The Empirical Content of a Roy Model of Social Interactions

In the previous section we have outlined a different way of thinking about social interactions using sorting and comparative advantage as the guiding principle of peer group organization. In this

[21]Note that if $\theta_N(i^*) \approx \theta_T(i^*)$, then agents will base their choice of sector (almost) exclusively on differences in social income, resembling our basic model. If, for instance, achievement is primarily determined by ability, or playing video games and bullying equally distract from studying, then it might very well be the case that θ_N and θ_T are of similar maginitude.

section, we consider the implications of the comparative advantage approach for the identification of peer effects. In doing so, we follow the literature and assume that there might exist other factors besides *social* payoffs that determine the utility of being a troublemaker or a nerd, e.g., personal and neighborhood characteristics, or the even behavior of one's peers, as has often been assumed. We then show how subsequent social group selection based on comparative advantage confounds identification.

To fix ideas, consider a student's choice of becoming a troublemaker, T, or a nerd, N. Let $\mathbf{X}_i$ be a set of individual level covariates, and let $\mathbf{Z}_m$ denote factors varying only at the school, neighborhood, or market level. The fraction of individuals associating with the troublemakers in market m is given by $\overline{y}_m$, and ν_{im} represents an error term known to the individual, but not the econometrician. Intuitively, ν_{im} captures all unobserved factors influencing the difference in utility between T and N. Student i chooses to become a troublemaker if and only if[22]

$$u\left(T;\mathbf{X}_i,\mathbf{Z}_m\right)-u\left(N;\mathbf{X}_i,\mathbf{Z}_m\right)=\kappa+\mathbf{X}_i'\boldsymbol{\beta}_0+\mathbf{Z}_m'\gamma_0+\alpha_0\overline{y}_m+\nu_{im}\geq 0. \tag{3.10}$$

Social wages and individual ability are typically not directly observable. Thus, the comparative advantage approach can be viewed as providing a more explicit theory of the error term. Following our theoretical model, decompose ν_{im} into the net market payoff from being a troublemaker and some other random variable:

$$\nu_{im}=\left(w_{Tm}\sigma_{Ti}-w_{Nm}\sigma_{Ni}\right)+\epsilon_i. \tag{3.11}$$

Note that only ϵ_i and σ_{ji}, $j\in\{N,T\}$, are possibly independent and identically distributed across individuals, whereas w_{Tm} and w_{Nm} (both of which are measured in utility units) vary only at the market or group level. Therefore, our theory stipulates the existence of group level unobservables.

Recall that not all parameters in the binary choice model are identified from cross-sectional data in the presence of group level unobservables (Blume, Brock, Durlauf, and Ioannides (2010); Brock and Durlauf (2007)). While $\boldsymbol{\beta}_0$ can be consistently estimated without imposing parametric assumptions (using methods outlined in Heckman 1990), γ_0 and α_0—the coefficients of interest in the majority of applied work—cannot. Nonidentification is due to the fact that ν_{im} depends on $\mathbf{Z}_m$

[22]To avoid confusion with our earlier assumption that mean behavior does not directly influence sector choice, note that the mean behavior in market m, $\bar{y}_m$, is irrelevant for an individual's choice of sector if α_0 is zero.

and $\overline{y}_m$ in an unknown way. Therefore, only the linear combination of market level observables and unobservables is identified (see Brock and Durlauf (2007) for a formal argument).

It is important to note that nonidentification as a result of group level unobservables is quite distinct from endogeneity due to systematic sorting of individuals into social markets (such as neighborhoods and classrooms), or the reflection problem, which poses that α_0 cannot be identified if $\mathbf{Z}_m$ and $\overline{y}_m$ are linearly dependent (Manski (1993)).[23] While applied researchers have often found clever strategies to deal with these two problems, group level unobservables have received much less attention. However, there are several notable exceptions: Cooley (2007) motivates her instrument in the presence of unobserved differences in teacher quality. Hoxby (2000) uses panel data to remove the effect of group level unobservables which do not vary over time; and Graham (2008) shows how conditional variance restrictions can be used to identify endogenous peer effects when individual and group level unobservables are uncorrelated.

To appreciate the consequences of group level unobservables, denote i's observed behavior by

$$y_i = \begin{cases} 1 & \text{if } u\left(T; \mathbf{X}_i, \mathbf{Z}_m\right) - u\left(N; \mathbf{X}_i, \mathbf{Z}_m\right) \geq 0 \\ 0 & \text{otherwise} \end{cases},$$

and consider the case in which mean behavior does not directly affect an individual's decision, i.e. $\alpha_0 = 0$. Assuming that $\text{Cov}\left(\mathbf{X}_i^*, \nu_{im}\right) = 0$, the Frisch-Waugh Theorem states that the probability limit of the ordinary least squares estimator of α_0 (from regressing y_i on $\mathbf{X}_i$, $\mathbf{Z}_m$, and $\overline{y}_m$) equals

$$\text{plim}\, \hat{\alpha}_{OLS} = \alpha_0 + \frac{\text{Cov}\left(\overline{y}_m^*, \nu_{im}\right)}{\text{Var}\left(\overline{y}_m^*\right)} = \frac{\text{Cov}\left(\overline{y}_m^*, \nu_{im}\right)}{\text{Var}\left(\overline{y}_m^*\right)},$$

where $\overline{y}_m^*$ denotes the residual from projecting $\overline{y}_m$ onto $\mathbf{X}_i$ and $\mathbf{Z}_m$. Only if $\overline{y}_m^*$ and ν_{im} are uncorrelated, will $\hat{\alpha}_{OLS}$ be consistent.

Yet, our Roy model of social interactions predicts that $\text{Cov}\left(\overline{y}_m^*, \nu_{im}\right) > 0$. To see this condition on $\mathbf{X}_i$ and $\mathbf{Z}_m$ and note that, according to (3.10), individual i in social market m chooses to become a troublemaker if and only if

$$\nu_{im} \geq \xi\left(\mathbf{X}_i, \mathbf{Z}_m\right) \tag{3.12}$$

[23] If $\mathbf{Z}_m$ exhibits sufficient variation and $\gamma \neq 0$, then the binary choice model of social interactions does not suffer from the reflection problem, as the limited range of the outcome rules out perfect linear dependence (Brock and Durlauf 2007).

where $\xi(\mathbf{X}_i, \mathbf{Z}_m) \equiv -(\kappa + \mathbf{X}_i'\boldsymbol{\beta}_0 + \mathbf{Z}_m'\gamma_0)$. Now, decompose ν_{im} into the market specific mean social payoff, $\overline{v}_m$, and deviations around the mean, $\widetilde{v}_{im}$, which are distributed according to some cumulative distribution function $\Phi_m(\cdot)$. That is, let $v_{im} = \overline{v}_m + \widetilde{v}_{im}$. With this notation in hand, $y_i = 1$ if and only if

$$\widetilde{v}_{im} \geq \xi(\mathbf{X}_i, \mathbf{Z}_m) - \overline{v}_m,$$

and the fraction of individuals who are troublemakers in market m is equal to

$$\overline{y}_m = \mathbb{E}_{\mathbf{X}_i}\{1 - \Phi_m(\xi(\mathbf{X}_i, \mathbf{Z}_m) - \overline{v}_m)\}.$$

Unless $\mathbf{X}_i$ and $\mathbf{Z}_m$ fully determine $\overline{v}_m$ (in which case there is no role for endogenous social interactions) it will be the case that $\frac{d\overline{y}_m^*}{d\overline{v}_m} > 0$, as $\frac{d\overline{y}_m}{d\overline{v}_m} > 0$. With this caveat in mind, it follows that $\text{Cov}(\overline{y}_m^*, \nu_{im}) > 0$.

The intuition for this result is straightforward. Under the assumptions of our model, a particular behavior will be more prevalent in markets in which the social net payoff to it is higher.[24] It follows that although mean behavior may not be a direct determinant of behavior, i.e. $\alpha_0 = 0$, linear-in-means estimates will be biased toward finding this form of peer effects—even under random assignment to social markets and if one resolves the reflection problem.

It is not the case, however, that estimates of peer effects are necessarily upward biased. Suppose, for instance, that $\overline{y}_m$ denotes mean test scores in social market m. Even if mean test scores were a sufficient statistics for the whole ability distribution, we would not be able to determine the covariance between $\overline{y}_m^*$ and ν_{im} without imposing further structure on the relationship between the fraction of troublemakers and residual academic achievement. It is still the case, however, that α_0 and γ_0 are not identified due to the presence of group level unobservables.

3.3.2 Evidence Consistent with a Roy Model Approach to Social Interactions

Lack of identification does not imply that the comparative advantage approach has no empirical content. As the net market payoff to troublemakers is a declining function of nerd ability, even

[24] Although, as shown in Section 3.2, a given level of mean behavior in a social market is consistent with *any* level of relative wages (depending on the intersection of relative supply and demand), the mean net social benefit of becoming a troublemaker, i.e. $\overline{v}_m$, combines the supply and and demand side into one statistic that *is* correlated with mean behavior.

purely ordinal information, such as a ranking of individuals, may be useful. For *any given* set of equilibrium prices, individuals with low cognitive ability are more likely to become troublemakers than ones with high nerd ability. If comparative advantage shapes social interactions, then individual behavior should depend on rank relative to others *within* the same market, and changes in rank induced by moves across markets should be systematically related to changes in behavior. Hence, our model predicts that, all else equal, an individual's behavior should be related to her rank within the relevant social market. For instance, children whose rank declines in transitioning from elementary to middle school (drawn from multiple elementary schools) should be more likely to develop behavioral problems than those whose rank increases.

The ideal data to test our theory would span multiple markets—say, schools or classrooms—and contain information on social wages, agents' choices of sector as well as all of their skills. With such data in hand we could test *directly* whether comparative advantage determines behavior by comparing potential 'social earnings' across sectors and relating them to agents' choices. Alternatively, data on only a subset of skills, social wages and individuals' choices of sector would allow us to follow Heckman and Sedlacek (1985), who combine information on individual characteristics, wages, sectoral choices, and aggregate wage bills to estimate a structural model of self-selection in the labor market, as well as the demand for observed and unobserved skill. We are unaware of such data.

In the absence of any information on social wages, and in lieu of imposing restrictive assumptions to ensure identification, we pursue the more modest goal of providing reduced form evidence which suggests that, within a market, individual behavior depends on one's rank. We leave the important question surrounding identification in the presence of group level unobservables for another occasion. The evidence we present below is purely suggestive, as there exist several competing models that share the same prediction. A trivial example is a model in which the intrinsic utility from being a nerd depends on one's class rank. Therefore, we urge caution when evaluating the empirical evidence in favor of the comparative advantage approach.

In what follows, we investigate the relationship between a student's relative academic ranking and behavioral outcomes in two large data sets: New York City Public Schools (NYCPS) administrative data from 2003/04 through 2008/09, and the National Education Longitudinal Study of 1988 (NELS). Since our theory predicts that this relationship can be non-linear we estimate semi-parametric specifications, as described in Yatchew (1998).

A. Evidence from New York City Public Schools

The New York City Public Schools (NYCPS) data contain student-level administrative information on approximately 1.1 million students across the five boroughs of the NYC metropolitan area. The data include student race, gender, free and reduced-price lunch eligibility, behavior, attendance, and matriculation with course grades for all students, as well as state math and English/Language Arts (ELA) test scores for students in grades three through eight. We have NYCPS data spanning the 2003/04 to 2008/09 school years. Summary statistics for the variables we use in our core specifications are displayed in Table 3.1.

Using the NYCPS data, we estimate models of the form

$$\Delta y_i = f(\Delta x_i) + \mathbf{X}_i'\beta + School_i + Year_i + \epsilon_i, \tag{3.13}$$

restricting our attention to the set of students who change schools in the transition from elementary to middle school. Our behavioral measure, y_i, in each year is an indicator equal to one if a student has at least one reported behavioral incident from that year and zero otherwise; $\Delta y_i \in \{-1, 0, 1\}$. The three most common behavioral incidents in our data are "engaging in an altercation or physically aggressive behavior with other student(s)," "behaving in a manner that disrupts the educational process (horseplay)," or "engaging in verbally rude or disrespectful behavior / insubordination."

A student's rank in fifth grade is the student's percentile ranking based on achievement on the New York State exam relative to other students who are in the same school in fifth grade.[25] We also compute each student's position relative to peers in her sixth grade school using the *fifth*

[25]The state math and ELA tests, developed by McGraw-Hill, are high-stakes exams conducted in the winters of third through eighth grade. Students in third, fifth, and seventh grades must score level 2 or above (out of 4) on both tests to advance to the next grade without attending summer school. The math test includes questions on number sense and operations, algebra, geometry, measurement, and statistics. Tests in the earlier grades emphasize more basic content such as number sense and operations, while later tests focus on advanced topics such as algebra and geometry. The ELA test is designed to assess students on three learning standards—information and understanding, literary response and expression, critical analysis and evaluation—and includes multiple-choice and short-response sections based on a reading and listening section, along with a brief editing task. Content breakdown by grade and additional exam information is currently available at
http://www.emsc.nysed.gov/osa/pub/reports.shtml.

Table 3.1: *Summary Statistics for NYCPS Data*

	Mean	SD	N
Change in behavioral incident indicator	.042	.318	256,168
Change in rank (English/Language Arts)	-.156	24.556	241,742
Change in rank (math)	-.215	22.711	253,504
Previous year test score (English/Language Arts)	661.372	36.948	241,742
Previous year test score (math)	668.141	41.627	253,504
White	.149	.356	256,159
Black	.314	.464	256,159
Hispanic	.394	.489	256,159
Asian	.139	.346	256,159
Other race	.004	.063	256,159
Male	.507	.500	256,160
Female	.493	.500	256,160
Free lunch	.830	.376	210,290
English Language Learner	.093	.290	253,641
Special education	.087	.282	253,641
Behavioral incident indicator	.089	.285	256,168
Previous year behavioral incidents	.083	.531	256,168
Observation from 2004-05 school year	.206	.405	256,168
Observation from 2005-06 school year	.194	.395	256,168
Observation from 2006-07 school year	.194	.396	256,168
Observation from 2007-08 school year	.201	.401	256,168
Observation from 2008-09 school year	.205	.403	256,168
Missing race	.000	.006	256,168
Missing sex	.000	.006	256,168
Missing free lunch status	.179	.383	256,168
Missing English Language Learner status	.010	.099	256,168
Missing special education status	.010	.099	256,168
Missing previous year behavioral incidents	.000	.000	256,168

Notes: Entries are means and standard deviations together with the number of valid observations for each variable we use in the NYCPS data. For further details about the NYCPS data see Appendix B.1.

grade test scores. This captures the student's ranking in the new school at the beginning of the school year; Δx_i denotes the difference between these two rankings. We report results using both math and ELA scores to compute the change in percentile. Finally, we include school fixed effects (for both a student's elementary and middle school), year fixed effects, and a standard set of covariates that includes the test score in the same subject from the previous year, an exhaustive set of race dummies, sex, free lunch eligibility, English Language Learner (ELL) status, and special education designation. By including these covariates we attempt to control for factors which plausibly influence changes in behavior and might be correlated with rank.

Our estimates of the link between changes in rank and changes in behavior are displayed in Figure 3.9. Independent of whether we calculate rank based on ELA or math scores, the behavior of students whose rank decreases in going from elementary to middle school worsens significantly compared to students whose relative standing improves. A student experiencing a 50 percentile decline in rank is approximately five percentage points more likely to have a behavioral incident on record than a student whose rank improves by 50 percentiles—with the estimated effect being slightly larger if we calculate rank based on math scores than if we do so based on ELA scores. Given sample means (and standard deviations) of .087 (.282) for sixth grade and .049 (.215) in fifth grade, our estimates indicate a 60–100% increase in the probability of a behavioral problem.

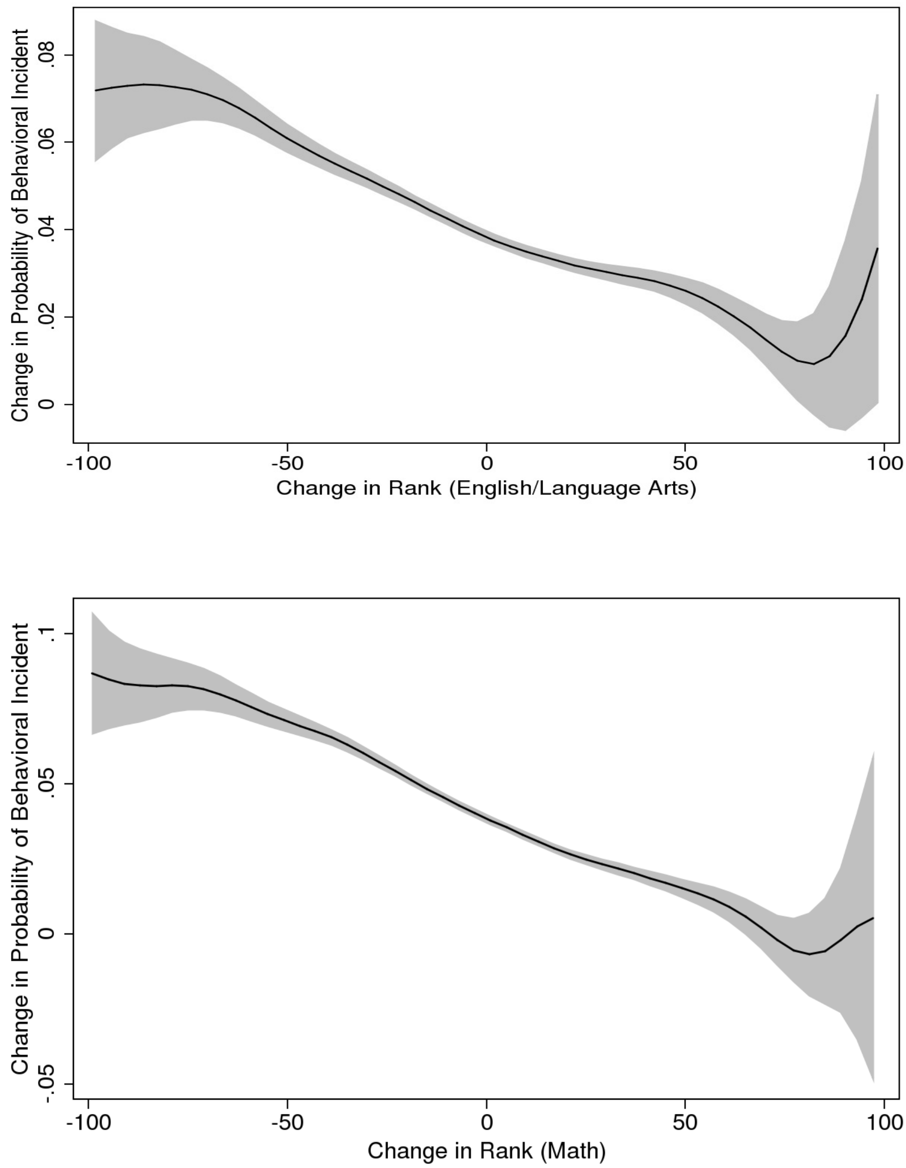
Although the NYCPS data allow us control for a students' natural proclivities to cause trouble by relating changes in behavior to changes in rank induced by the transition to middle school, there exists the possibility that our results are driven by systematic school choice. That is, students who chose an academically less challenging environment might have experienced less of an increase in behavioral problems, even if their rank had not improved.

To address the concern of systematic sorting into schools, we instrument for a student's change in rank with their predicted change in rank based on the school they were zoned to attend (given their residential address).[26] More specifically, we estimate two-stage least squares (2SLS) specifications corresponding to:

$$\Delta y_i = \alpha \Delta x_i + \mathbf{X}_i' \beta + School_i + Year_i + \epsilon_i \,, \tag{3.14}$$

[26]For more information on New York's school choice plan, see http://schools.nyc.gov/ChoicesEnrollment/default.htm.

Figure 3.9: *Evidence from New York City Public Schools*



Notes: Panels show non-parametric estimates and the associated 95%-confidence intervals of the effect of a change in a student's class rank (in going from elementary to middle school) on the change in an indicator variable for whether she was involved in a behavioral incident, cf. equation (12). The top panel constructs rank based on English/Language Arts (ELA) test scores, whereas the lower one uses math test scores. Estimates are obtained using the differencing procedure in Yatchew (1998) and local-mean smoothing with a Gaussian kernel and a bandwidth of 10.

where the first stage is given by

$$\Delta x_i = \delta \widehat{\Delta x_i} + \mathbf{X}_i' \gamma + School_i + Year_i + \nu_i,$$

and $\widehat{\Delta x_i}$ denotes student i's counterfactual change in rank at the beginning of sixth grade had all students attended the schools for which they were zoned. More specifically, let $x_{i,t-1}$ denote student i's test score in fifth grade and let $rank_I(x_{i,t-1})$ be the percentile ranking of a student with score $x_{i,t-1}$ among the set of students I, given their respective test scores at $t-1$. Then,

$$\widehat{\Delta x_i} \equiv rank_{S_{i,t}}(x_{i,t-1}) - rank_{S_{i,t-1}}(x_{i,t-1}),$$

where $S_{i,t-1}$ and $S_{i,t}$ are the sets of students who are zoned for the same elementary and middle school as i, respectively.

Tables 3.2 and 3.3presents 2SLS estimates of the partial correlation between school rank and behavior, as well as the corresponding OLS estimates for comparison. In Table 3.2 we use ELA scores to construct rank, whereas math scores are used in Table 3.3. Based on the OLS point estimates one would expect a student experiencing a 50 percentile decline in rank to be about 3.5 (panel A) or 5–6 (panel B) percentage points more likely to have a behavioral incident on record than a student whose rank improves by 50 percentiles—consistent with our previous semi-parametric results.

Due to the large number of observations, our OLS estimates are very precise. Unfortunately, this is not the case when we estimate equation (3.14) by 2SLS. Although the first stage F-statistic is well above conventional critical values (Stock and Yogo (2002)), our instrument explains very little residual variation in the excluded variable, as evidenced by small values of Shea's R^2 (Shea (1997)). One potential explanation for this is that only 46.0% (53.6%) of students attend the middle (elementary) school for which they are zoned.

Nevertheless, not including school fixed effects, the 2SLS estimates are remarkably similar to their OLS counterparts; and statistically significant at 1%-level. If, however, we include school fixed effects, the point estimates shrink by more than half and are statistically indistinguishable from zero, though still negative. Given that our instrument, $\widehat{\Delta x_i}$, explains less than one percent of the residual variation in Δx_i when school fixed effects are included, we strongly urge caution when interpreting the results presented in Tables 3.2 and 3.3. In order to better account for the

Table 3.2: *Estimates of the Relationship between Individuals' Rank and Behavior: ELA*

Independent Variable	Δ Behavioral Incident OLS	Δ Behavioral Incident OLS	Δ Behavioral Incident 2SLS	Δ Behavioral Incident 2SLS
ΔRank (÷100)	-.033	-.036	-.047	-.022
	(.003)	(.003)	(.017)	(.041)
Test Score at Previous School (÷100)	-.030	-.031	-.034	-.028
	(.002)	(.002)	(.005)	(.010)
Male	.019	.019	.018	.019
	(.001)	(.001)	(.001)	(.002)
Black	.007	.025	.006	.024
	(.002)	(.003)	(.002)	(.003)
Hispanic	-.005	.005	-.006	.005
	(.002)	(.002)	(.002)	(.003)
Asian	-.021	-.014	-.021	-.014
	(.002)	(.002)	(.002)	(.003)
Other Race	.001	.022	-.004	.018
	(.012)	(.012)	(.012)	(.012)
Free Lunch	.012	.011	.011	.011
	(.002)	(.002)	(.002)	(.002)
English Language Learner	-.010	-.009	-.011	-.009
	(.003)	(.003)	(.003)	(.004)
Special Education	.010	.005	.006	.005
	(.003)	(.003)	(.004)	(.006)
Year Fixed Effects	Yes	Yes	Yes	Yes
School Fixed Effects	No	Yes	No	Yes
First Stage F-Stat	—	—	5,117	1,224
Shea's Partial R-Squared	—	—	.027	.006
R-Squared	.005	.062	.005	.062
Number of Observations	241,734	241,734	233,247	233,247

Notes: Entries are coefficients and standard errors from estimating the linear model, equation (13), by ordinary least squares and two-stage least squares, i.e. equation. The dependent variables is listed at the top of each column. The instrument for Δ Rank is the predicted change in rank based on school zoning regulations, as explained in the text and Appendix B.1. Student rank is calclulated based on ELA test scores. Heteroskedasticity robust standard errors are reported in parentheses. In addition to the variables included in the table, indicator variables for missing values on each covariate are also included in the regressions. See Appendix B.1 for the precise definition and source of each variable.

Table 3.3: *Estimates of the Relationship between Individuals' Rank and Behavior: Math*

Independent Variable	ΔBehavioral Incident OLS	ΔBehavioral Incident OLS	ΔBehavioral Incident 2SLS	ΔBehavioral Incident 2SLS
ΔRank (÷100)	-.051	-.060	-.051	-.019
	(.003)	(.003)	(.016)	(.036)
Test Score at Previous School (÷100)	-.027	-.030	-.027	-.023
	(.002)	(.002)	(.004)	(.006)
Male	.022	.021	.021	.021
	(.001)	(.001)	(.001)	(.001)
Black	.007	.024	.006	.024
	(.002)	(.003)	(.002)	(.003)
Hispanic	-.005	.004	-.005	.004
	(.002)	(.002)	(.002)	(.002)
Asian	-.017	-.010	-.017	-.012
	(.002)	(.002)	(.002)	(.003)
Other Race	.003	.024	-.000	.021
	(.012)	(.011)	(.012)	(.012)
Free Lunch	.013	.011	.013	.011
	(.002)	(.002)	(.002)	(.002)
English Language Learner	-.007	-.007	-.006	-.006
	(.002)	(.002)	(.002)	(.002)
Special Education	.006	.001	.005	.003
	(.003)	(.003)	(.004)	(.004)
Year Fixed Effects	Yes	Yes	Yes	Yes
School Fixed Effects	No	Yes	No	Yes
First Stage F-Stat	—	—	7,155	1,903
Shea's Partial R-Squared	—	—	.036	.009
R-Squared	.006	.061	.006	.060
Number of Observations	253,496	253,496	245,298	245,298

Notes: Entries are coefficients and standard errors from estimating the linear model, equation (13), by ordinary least squares and two-stage least squares, i.e. equation. The dependent variables is listed at the top of each column. The instrument for Δ Rank is the predicted change in rank based on school zoning regulations, as explained in the text and Appendix B.1. Student rank is calclulated based on Math test scores. Heteroskedasticity robust standard errors are reported in parentheses. In addition to the variables included in the table, indicator variables for missing values on each covariate are also included in the regressions. See Appendix B.1 for the precise definition and source of each variable.

possibility of bias due systematic sorting of students into schools, we turn the National Education Longitudinal Study.

B. Evidence From the National Educational Longitudinal Study

The National Education Longitudinal Study of 1988 (NELS) was initiated in 1988 with a cohort of 24,599 eighth graders, who were then resurveyed through four follow-ups in 1990, 1992, 1994, and 2000. The available information on these students covers a wide range of topics including: school, work, and home experiences; educational resources and support; the role in education of their parents and peers; neighborhood characteristics; educational and occupational aspirations; as well as other student perceptions. For the first three waves, students also completed achievement tests in reading, social studies, mathematics and science. In addition to collecting information on students' course work and grades in high school as well as postsecondary transcripts, their teachers, parents, and school administrators were also surveyed. Table 3.4 displays summary statistics for all variables we use in our analysis.

We examine NELS data from 1988 and 1990, when students were in eighth and tenth grade. An important limitation of the NELS data is that only 25 students per school were surveyed, yielding a noisy measure of rank. To lessen the impact of measurement error, we limit our sample to students in classrooms with at least five observations.[27] Yet, NELS allows us take advantage of the fact that the data include teacher reports on behavior and student self-reported grades from exactly two subjects in the same year. By using a model that relates changes in a student's behavior across classrooms to changes in her rank we can implicitly account for students' natural tendencies to cause trouble and rule out that systematic sorting into schools drives our results.[28] More specifically, we estimate a model of the form

$$\Delta y_{i,t} = f(\Delta x_{i,t}) + \mathbf{X}'_{i,t}\beta + Grade_i + \epsilon_{i,t} \tag{3.15}$$

where $y_{i,s}$ is an indicator for whether a teacher in subject s reports that student i had any behavioral problems, and $\Delta y_{i,t}$ refers to the difference in this indicator across subjects (Math/Science minus

[27]We obtain qualitatively identical results for alternative threshold levels of ten and zero.

[28]Students strategically sorting into classrooms based on other unobservables is still a potential concern.

Table 3.4: *Summary Statistics for NELS Data*

	Mean	SD	N
Difference in behavioral incident dummy (eighth grade)	.007	.519	19,782
Difference in behavioral incident dummy (tenth grade)	.008	.548	10,506
Behavioral incident dummy (eighth grade)	.387	.487	19,782
Behavioral incident dummy (tenth grade)	.557	.497	10,523
Difference in behavioral incident factor (eighth grade)	.003	.951	19,709
Difference in behavioral incident factor (tenth grade)	.016	.938	10,399
Behavioral incident factor (eighth grade)	-.024	.983	19,761
Behavioral incident factor (tenth grade)	-.020	.978	10,485
Difference in class rank (eighth grade)	-.652	33.960	19,782
Difference in class rank (tenth grade)	-.980	35.599	10,523
Mean test score (eighth grade)	.060	.868	19,213
Mean test score (tenth grade)	.093	.870	10,241
Male	.497	.500	21,297
White	.694	.461	21,297
Black	.111	.314	21,297
Hispanic	.118	.322	21,297
Asian	.058	.233	21,297
English Language Learner	.027	.163	21,297
Parents married	.721	.449	21,297
Parents' education: less than high school	.096	.295	21,145
Parents' education: high school graduate	.192	.394	21,145
Parents' education: some college	.403	.490	21,145
Parents' education: college graduate	.153	.360	21,145
Parents' education: M.A.	.096	.295	21,145
Parents' education: Ph.D., M.D., other	.060	.238	21,145
Public school (eighth grade)	.792	.406	21,297
Catholic school (eighth grade)	.102	.303	21,297
Independent/other private school (eighth grade)	.106	.308	21,297
School in urban area	.289	.453	21,297
School in rural area	.290	.454	21,297

Notes: Entries are means and standard deviations together with the number of valid observations for each variable we use in the NELS data. For further details about the NELS data see Appendix B.2, or the NELS website currently located at http://nces.ed.gov/surveys/nels88

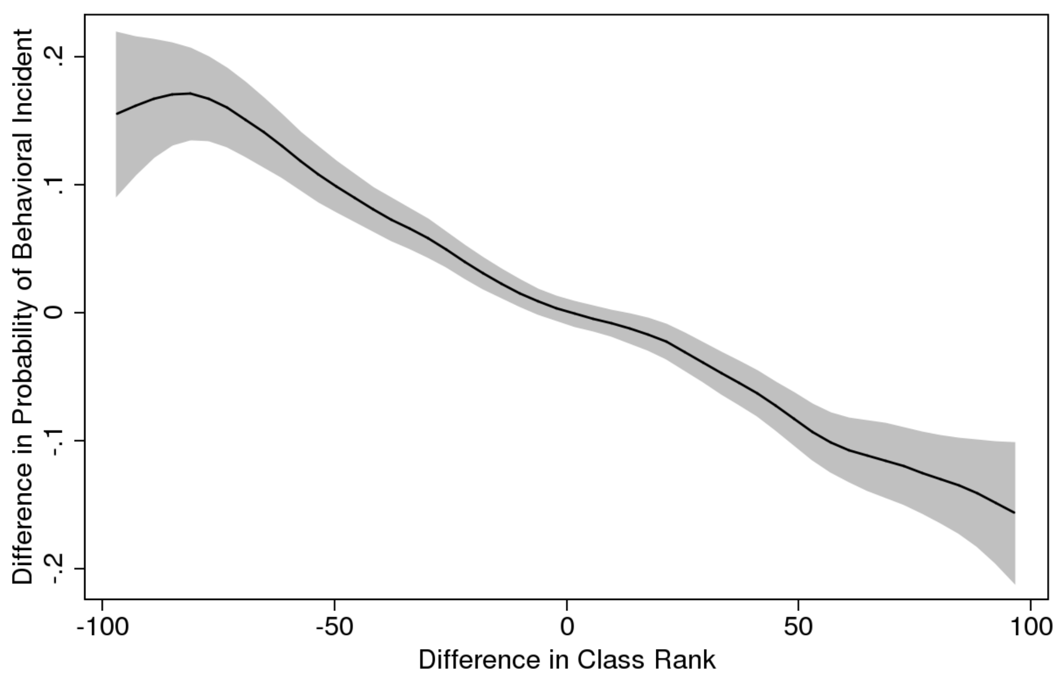
English/History) within the same year. Teachers were asked whether the student had a problem in any of six different categories: the student performed below his ability, the student did not complete homework, the student was frequently absent, the student was frequently tardy, the student was inattentive, or the student was disruptive. Our indicator variable is equal to one if the teacher reported that the student had at least one of these behavioral problems. It is important to note that the NELS measure of behavioral problems encompasses a far more benign set of 'offenses' than those typically reported in NYCPS. We use student self-reported grades to compute subject-specific rank $x_{i,s,t}$, and let $\Delta x_{i,t}$ denote the difference in these ranks across subjects within the same year. Moreover, $\mathbf{X}_{i,t}$ includes: the mean score across subjects from the same year and its square, race, sex, English Language Learner status, indicator variables for parents' marital status, indicator variables for parents' education, indicator variables for school type (public, Catholic, or other private), indicator variables for school location (urban, suburban, or rural), indicator variables for socioeconomic status quartiles, birth year indicators, and birth month indicators; $Grade_i$ marks a grade level fixed effect.

As was the case in the NYCPS data, we find that changes in a student's rank within a social market are related to changes in her behavior (see Figure 3.10). For instance, students whose rank is 50 percentiles lower in English class than in Math class are estimated to be approximately ten percentage points more likely to act out in the former than the latter. Taken at face value rank appears to have a substantial influence on behavior.[29]

Broadly summarizing, the results presented in this section suggest that students' behavior deteriorates as their academic rank declines—whether across schools, or across subjects. By controlling for both prior test score levels and school fixed effects, this evidence suggests that students' behavior is being determined in part by their comparative advantage in these activities relative to that of their peers.

[29]In NELS the sample mean (and standard deviation) of our indicator for having at least on behavioral incident is .427 (.495) in math, .402 (.490) in history, .426 (.495) in science, and .429 (.495) in English class. Every student has information on at most two of these subjects. See also Table 3.4 and the description of NELS in Appendix B.2. Instead of using an indicator variable for whether the teacher reports any behavioral incidents, we have also constructed a summary index of children's behavior by factor analyzing different teacher reported behaviors. For both outcomes our results are qualitatively identical.

Figure 3.10: *Evidence from the National Educational Longitudinal Study*



Notes: The figure shows non-parametric estimates and the associated 95%-confidence intervals of the effect of differences in a student's course-specific rank on the difference in two course-specific behavioral outcomes, cf. equation (14). Estimates are obtained using the differencing procedure in Yatchew (1998) and local-mean smoothing with a Gaussian kernel and a bandwidth of 7.5.

3.4 Concluding Remarks

While social scientists have long been concerned with the influence of social interactions, empirical estimates of peer effects vary widely in the literature. Using different sources of (plausibly) exogenous variation some studies find negligible effects, others find effects that are positive and linear in mean peer characteristics, and occassionally peer effects have been found to be negative. We develop a Roy model of social interactions which, through comparative advantage, has the potential to provide a parsimonous explanation for the disparate empirical evidence. In our model 'peer effects' arise endogenously due to the sorting of individuals *within* narrowly defined social settings, such as neighborhoods or classrooms. Consequently, the comparative advantage approach has important implications for the (non)identification of peer effects—even if individuals are randomly assigned to social markets. In addition, since an unobserved wage is the critical determinant of selection, assigning students to an environment with higher academic abilities is no guarantee that they will face higher wages for academic effort. This places severe constraints on the external validity of any randomized trial.

Our data exercise provides suggestive evidence that the key prediction distinguishing our model from traditional approaches is borne out in two datasets. However, it is important to note that other models which predict both positive *and* negative peer effects, might also be able to reconcile our empirical evidence as well as the existing literature.

At its core, our theory builds upon impressive literatures designed to understand the evolution of earnings, the (hedonic) pricing of skills, and the assignment of workers to firms. The novelty in our approach lies in the application of these classic methods to develop a theory of social interactions to characterize equilibria in different social markets. The insights emerging from this approach may also be useful in understanding a variety of other social phenomena, one particular example being identity choice.

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Appendix A

Data Appendix for Chapters 1 and 2

Data on Divestitures

Data on divestitures is compiled from the "Electric Utility Plants Sold/Transferred and Reclassified as Non-utility Plants" Tables across various years of the March Issue of EIA's "Electric Power Monthly" report. It is also possible to identify month of divestiture prior to 2002 because plants cease reporting fuel costs at that time. A third source of divestiture date is a change in regulatory status reported on Form EIA-906, "Power Plant Report." In the relatively uncommon case that these dates disagree, I rely first on the cost data (a signal of operational changes at the plant), then the sale data, and finally the "Power Plant Report" data.

Table A.1 breaks down this history of coal-fired plant divestitures by state. Divestiture of utility-owned plants in a state was usually complete following passage of passing restructuring laws. Not all states that restructured have coal-fired plants to use in this study. Although California restructured its electricity markets, its IOUs did not own any coal-fired capacity. Washington, DC was also restructured but its two coal-fired plants are used sufficiently little to avoid fuel delivery reporting requirements. All New England states except Vermont restructured their electricity markets, but Maine and Rhode Island do not have coal-fired generating assets. New Hampshire did not require divestiture of the two coal-fired plants owned by Public Service of New Hampshire, and these plants continue to report costs after the introduction of retail competition.

There have also been a number of divestitures in states that remain otherwise rate-regulated. The plants divested in Indiana, and Virginia were owned by IOUs based in restructured states,

Table A.1: *Summary of Coal Plant Divestitures by State*

State	Plants (Divested)	Fraction of IOU Divested	Fraction of Capacity Divested	Mean Sale Date [s.d.]
Texas	17 (9)	0.69	0.60	8/2002 [13.69]
Connecticut	1 (1)	1.00	1.00	5/1999 [.]
Delaware	2 (2)	1.00	1.00	7/2001 [0.00]
Maryland	7 (7)	1.00	1.00	10/2000 [3.09]
Illinois	22 (19)	1.00	0.95	10/2000 [18.57]
Indiana	24 (1)	0.05	0.02	9/2001 [23.14]
Massachusetts	4 (4)	1.00	1.00	12/2000 [47.45]
Montana	3 (2)	0.67	0.98	1/2000 [0.00]
New Jersey	5 (4)	1.00	0.99	9/2002 [38.19]
New York	10 (8)	0.89	0.92	8/1999 [6.46]
Ohio	25 (8)	0.38	0.26	2/2002 [29.28]
Pennsylvania	21 (21)	1.00	1.00	7/2000 [14.09]
Virginia	9 (1)	0.11	0.10	2/2002 [29.41]
Washington	2 (1)	1.00	0.97	5/2000 [0.00]
Divest States Total	152 (88)	0.65	0.33	7/2001 [23.71]

Notes: Coal-fired cogeneration plants in CA were not affected by restructuring legislation (4 plants). Other restructured states without reporting coal plants include ME, VT, RI, and DC. NH did not require divestiture (2 plants) Sources: "Electric Power Monthly" (March, various years), EIA-423/923 and EIA-906.

and were forced to sell for this reason. Montana has suspended restructuring, but Montana Power Company assets were divested in 2000 after its failed telecom investments during the dot-com bust led the company in to bankruptcy. The Centralia station in Washington state was sold amidst conflict among the plant's eight co-owners.

Divestiture status in Ohio and Texas varies by utility service area. The only IOU plants in Texas that remain to be divested belong to Southwestern Electric Power Company, which is connected to a separate grid from the rest of the state. The lack of markets available in this service area has delayed divestiture. In Ohio, two Duquesne Light Co. coal-fired plants were divested in 2000 as part of Pennsylvania's restructuring program. Although Ohio implemented retail choice in 2000, FirstEnergy's plants in Ohio would not be divested until 2005. Plans to divest of the remaining IOU plants in Ohio have been tied up between the Public Utilities Commission of Ohio (PUCO) and the courts since that time. The owners of these plants remain rate-regulated and require approval PUCO approval to change electricity prices.

Coal Prices

This study uses detailed data on coal deliveries to power plants from the Energy Information Administration (Forms EIA-423, "Monthly Report of Cost and Quality of Fuels for Electric Plants," and EIA-923, "Power Plant Operations Report") and Federal Energy Regulatory Commission (Form FERC-423, "Monthly Report of Cost and Quality of Fuels for Electric Plants"). This is shipment-level data, reported monthly for nearly all of the coal burned for the production of electricity in the United States (all facilities with a combined capacity greater than 50MW are required to report). The data records the county or mine of origin, whether purchased on the spot market or long-term contract, characteristics of the coal (heat, sulfur and ash content), rank (bituminous, etc.), and the price per million British thermal units (MMBTU). Although data on prices is redacted from public release for non-utilities, restricted-access data on prices was made available for this study under a non-disclosure agreement with EIA.

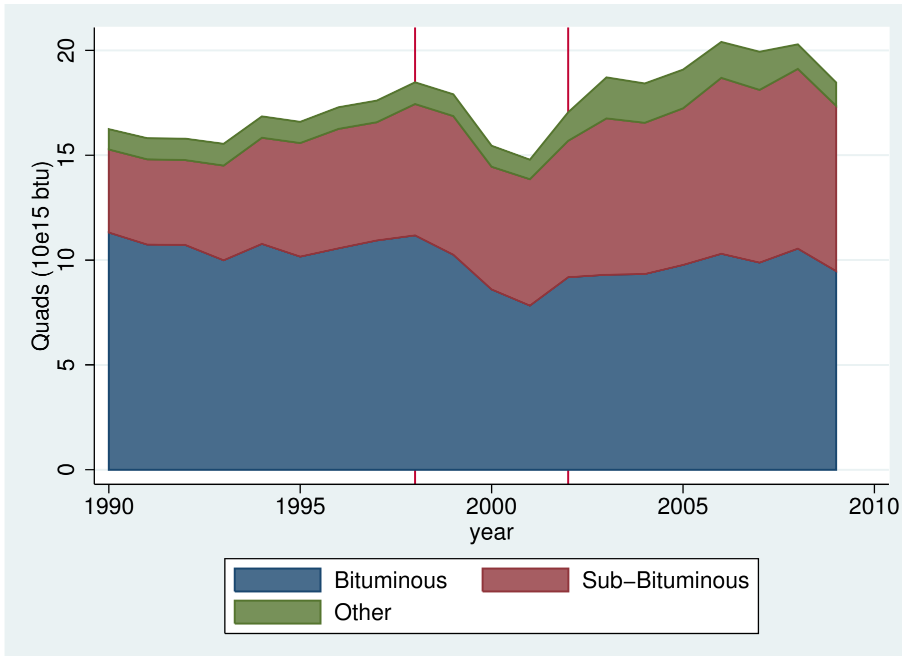
One critical caveat is that plants were no longer required to report to FERC upon divestiture, and EIA did not assert their authority under the Federal Energy Administration Act of 1974 to resume collection from non-utility plants until 2002.[1] Plants that were sold before 2002 therefore have a gap in reporting following divestiture. With most divestitures occurring between 1999 and 2001, this results in a two year gap on average. An exception is for the six FirstEnergy plants in Ohio that stopped reporting once retail competition began in June of 2000, but did not resume reporting until actual divestiture at the end of 2005. All results are robust to the exclusion of these plants.

Coal delivered to combined heat and power plants (4% of reported coal deliveries after 2002) is not included in any of the analysis. These are plants that also sell steam, either for heating or industrial processes. One reason is practical: 36 of 49 coal-fired co-generation plants were not required to report until 2002, so they lack data in the pre-divestiture baseline period. The second is that it is unclear how to categorize the regulatory structure these plants face: a plant owned by an IOU may be free to privately contract for steam to nearby industrial plants. In addition, four small (typically produced <50MWh/month) facilities that were divested, but never report

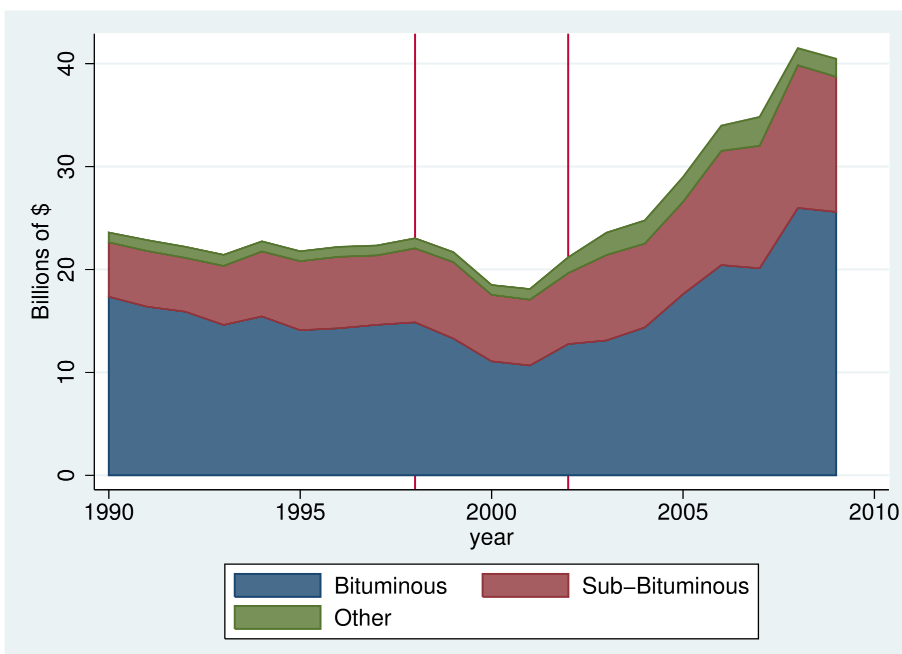
[1] When switching to Form 923 in 2008, the EIA began collecting monthly data from a sample of plants, and a census annually. Monthly data is estimated by EIA from plants that only submitted the annual form. This change applied more significantly to gas-based generators, as more than 97% of coal deliveries continued monthly reporting.

Figure A.1: *Total Heat Content and Cost of Coal Deliveries by Rank, 1990-2009*

(a) *Total Heat Content of Coal Deliveries*



(b) *Total Cost of Coal Deliveries*



Note: Vertical lines denote the year in which divestitures begin (1998), and when reporting for non-utilities commences (2002). Source: Forms EIA-423,923 and FERC 423.

post-divestiture are also dropped. They are the Hickling and Jennison plants in NY, Grand Tower in IL, and Edgewater in OH.

Figure A.1a shows the total heat content of coal deliveries reported to FERC/EIA from 1990-2009. The vertical lines represent the points at which divestitures begin in 1998, and when reporting for divested plants resumes in January 2002. There is clearly a substantial amount of non-reporting induced by divestiture. Aside from this dip, there is a 15-25% increase in coal delivered over this 20 year period.[2] It is important to note that nearly all of this came from an increase in production at existing facilities, not entry of new plants.

Another feature of Figure A.1a worthy of note is the expansion of sub-bituminous coal, both in levels and as a share of coal consumed for electric power. The Clean Air Act of 1990 created a cap-and-trade program to reduce sulfur emissions from electricity generating and large industrial units. Putting a price on sulfur increased the relative value of low-sulfur sub-bituminous coal (95% of sub-bituminous coal mined in the United States in 2009 was from the Powder River Basin (PRB) in Wyoming). Switching to PRB coal provided an alternative to building capital-intensive scrubbers to reduce sulfur emissions. Technological improvements as demand for PRB coal expanded further reduced the price of extraction, making PRB coal a potentially economical choice regardless of environmental compliance considerations. Shipments of PRB coal more than doubled over the twenty year period of study, accounting for about 40% of the coal heat delivered in 2009.

Plant-Level Data

Data on generator nameplate capacity and vintage comes from Form EIA-860, "Annual Electric Generator Report," while data on installed abatement equipment is from Form EIA-767, "Annual Steam-Electric Plant Operation and Design Data" and EIA-923, "Power Plant Operations Report." Annual capacity factor is the annual net generation reported on FormEIA-906/759, "Power Plant Report" divided by maximum potential output as determined by facility nameplate rating. This form is also the source for analysis on changes in output at the facility-level. Utility-specific implementations of Incentive Regulation programs is from Sappington and Pfeifenberger (2001) with updates from Guerriero (2010). This is linked to the plant-level data by the utility identifiers in the "Power Plant Report" data.

[2]The drop-off in 2009 is the combined effect of the economic downturn and displaced generation due to the fall in natural gas prices.

Data on geographic coordinates of power plants is from the Environmental Protection Agency's eGrid database.

Unit-Level Data

Unit-specific characteristics are assembled using the crosswalks between unit components provided in Form EIA-767, "Annual Steam-Electric Plant Operation and Design Data" available from 1990-2005. The data on this form was later compiled on Form EIA-923, "Power Plant Operations Report" after a gap in reporting for 2006.[3] The effects of this gap can be mitigated by the fact that scrubber installation date is collected, so status in the missing year can be inferred from prior and subsequent years. Power generating stations have been required to file these forms with EIA regardless of regulatory status,[4] so this series does not suffer from the intermittent non-reporting present in the fuel price data. Unit-level generator nameplate capacity and vintage comes from Form EIA-860, "Annual Electric Generator Report."

As with the generating facilities themselves, there has also been limited entry and attrition at the unit level. As a fraction of nameplate capacity, 92% of units reporting in 2009 also reported when the series began in 1990 (85% of units). These numbers increase to 95% and 93% respectively when accounting for the expanded coverage among combined heat and power units in 2002. Attrition was similarly rare, with 96% of capacity and 87% of units reporting in 1990 continuing to report in 2009.

It is worth noting that is that it is not uncommon for facilities to have both scrubbed and un-scrubbed units operating at the same plant. This can be seen by comparing the number for *any* scrubber present at the facility in Table 1.1, and the unit-level statistics in Table 1.3.[5] The differences between divested and non-divested units are otherwise similar to those found at the plant level, and largely eliminated in the matched sample.

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[3]Plants with a combined nameplate capacity less than 50 MW are not required to report fuel prices (Form EIA-423/923), while all facilities with a capacity greater than 10 MW are required to report generating unit configurations and operations (Form EIA-767/923). The discrepancy amounts to an infinitesimal share of production and capacity.

[4]Form EIA-767 expanded coverage to a handful of combined heat and power plants in 2002.

[5]While scrubbers had only been installed on a small fraction of generating units in 1997, these units were disproportionately large. In 1997 28% of U.S. coal-fired capacity was scrubbed for sulfur emissions. This has grown to nearly half by 2009.

Mine-Level Data

Data on mine labor productivity is from the Mine Safety and Health Administration's "Quarterly Mine Employment and Coal Production Report" (MSHA-7000-2). Figure A.2 shows the trends in production and labor hours over the sample period. The main development over the last twenty years has been the explosion of production from the Powder River Basin (PRB) in Wyoming. This has more than offset the decline of output elsewhere, so that there has been a modest increase in coal production overall. The shift in output has been accompanied with a sharp decline in mining employment, which has only rebounded slightly since 2005. The 1990's saw sharp increases in labor productivity all around–from expanding output faster than employment in the PRB, and by reducing employment faster than output in the East. It requires about seven times less labor to extract a ton of coal in the PRB.

Wages are calculated by adding up the quarterly hours reported in the MSHA data by FIPS county, and merging this data with the quarterly wage bill in the coal mining sector as reported in the "Quarterly Census of Employment and Wages" from the Bureau of Labor Statistics.[6] Wage rates are calculated at the county level by dividing the total county wage bill by total hours.

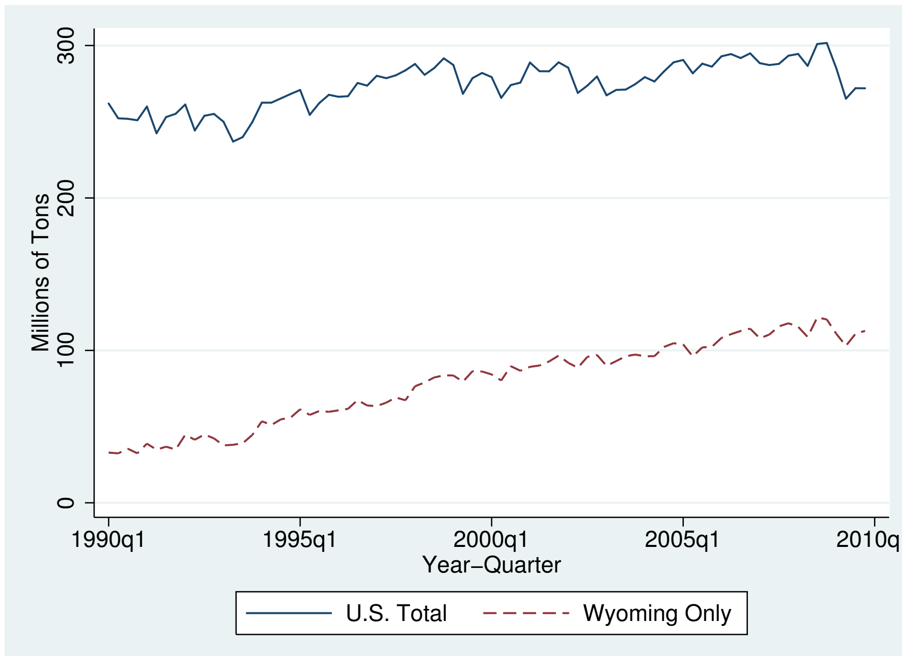
The thickness of coal seams is from MSHA's "Mine Dataset," which contains descriptive data on all mines under MSHA's jurisdiction since 1970. To calculate the depth of mine seams, I used a Perl script to collect the universe of stratigraphic data from the U.S. Geological Survey's "National Coal Resources Data System." The combined USTRAT and COALQUAL databases consist of over 200,000 geo-coded core samples taken by federal and state geologists in order to map U.S. coal deposits. Among the many parameters collected from these core samples is the depth of coal deposits. I use these points to create a surface of estimated seam depth using a spline to interpolate between points using the geoprocessing toolkit of ArcGIS 10.0. I then intersect the coordinates of mines with this surface to estimate the depth of coal deposits at each mining site.

The EIA only began collecting source mine identifiers (MSHA ID) on the fuel delivery data in 2008. From 1990-2001, I link deliveries to the name of the supplier listed in EIA's Coal Transportation Rate Database (CTRD) based on facility, county of coal origin, and the characteristics of the coal reported in both the CTRD and EIA-423 data. The name of the supplier is explicitly

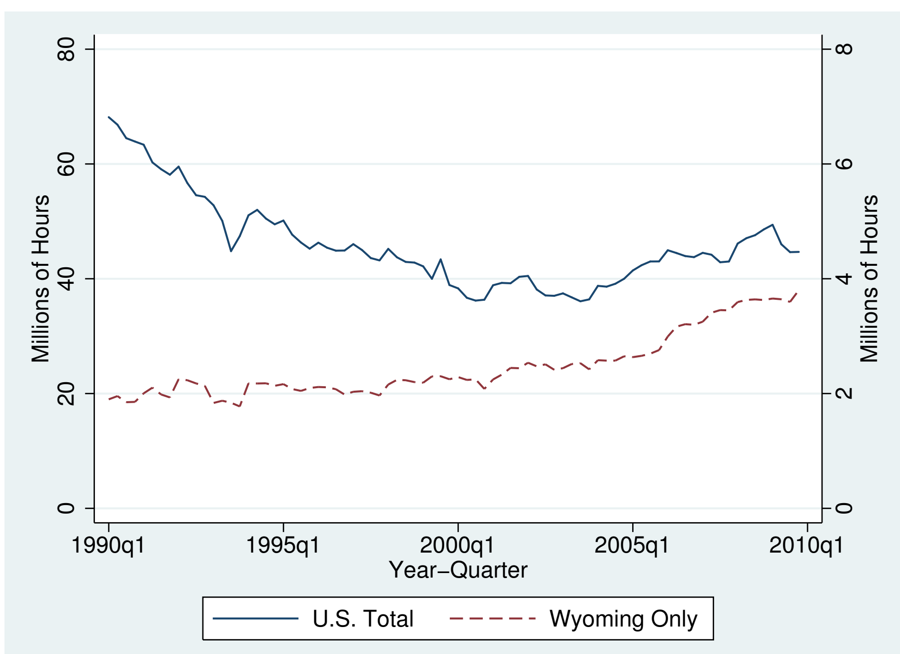
[6] Coal mining employment is reported under the four-digit NAICS code, "2121."

Figure A.2: *U.S. Coal Production and Labor Demand, 1990-2009*

(a) *Production*



(b) *Labor Input*



Source: Form MSHA-7000-2.

listed in the EIA-423 data beginning in 2002. Deliveries and mine characteristics are therefore connected at the county-supplier level.

Appendix B

Appendix for Chapter 3

B.1 New York City Public Schools Data

Demographic Variables

Demographic variables that should not vary from year to year (race, gender) were pulled from New York City enrollment files from 2003/04 through 2008/09, with precedence given to the most recent files. Race consisted of the following categories: black, Hispanic, white, Asian, and other race. These categories were considered mutually exclusive. The "other race" category consisted of students who were coded as "American Indian." Gender was coded as male, female, or missing.

Demographic variables that may vary from year to year (free lunch status, English Language Learner status, and special education designation) were only pulled from the enrollment file corresponding to the same year as the observation. A student was considered eligible for free lunch if he was coded as "A" or "1" in the raw data, which corresponds to free lunch, or "2", which corresponds to reduced-price lunch. A student was considered non-free lunch if the student was coded as a "3" in the NYC enrollment file, which corresponds to full price lunch. All other values, including blanks, were coded as missing. For English Language Learner status, a student was given a value of one if he was coded as "Y" for the limited English proficiency variable. All other students in the NYC data were coded as zero for English Language Learner status. Special education was coded similarly.

New York State Test Scores

NYC state test scores were constructed from the NYC test score files for 2003/04 through 2008/09 for English/Language Arts (ELA) and math. School-wide rankings were constructed based on these test scores.

Behavior

The number of behavioral incidents for each student was determined from NYC files listing all recorded behavioral incidents from 2004/05 through 2008/09. Students not listed in this file but with a valid test score from the same year were assumed to have zero behavioral incidents. We constructed a behavioral incident indicator with a value of one if the student was listed for a behavioral incident in the file from the relevant year, zero if the student had a valid test score from the same year, and missing otherwise.

B.2 National Educational Longitudinal Study Data

Demographic Variables

Demographic variables were taken from the baseline year of the survey. These included: race, sex, English Language Learner status, parents' marital status, parents' education, school type (public, Catholic, or other private), school location (urban, suburban, rural), socioeconomic status, birth month, and birth year.

Behavior

Behavior variables were constructed using data from teacher reports on individual students. Teachers were asked to indicate whether the student had problems in each of the following areas: the student performs below his ability, the student does not complete homework, the student is frequently absent, the student is frequently tardy, the student is inattentive, or the student is disruptive. In the baseline year (eighth grade), each student had one teacher report from either Math or Science and another from either English or History, for a total of two teacher reports. Similarly, each student had two reports from the first follow-up year (tenth grade). Teacher reports were also administered in the second follow-up year (twelfth grade) but only in one subject, so these reports are excluded from our analysis, which takes advantage of within-year across-subject variation. For each student, we constructed an indicator that is equal to one if the student's teacher reports that the student has a problem in at least one of the six categories and zero otherwise. The outcomes used for our analysis are the within-year differences across subjects in the behavioral indicator.

Grades

The dataset contains self-reported grades for the baseline, first follow-up, second follow-up years. In the baseline year, students were asked to report for each subject (Math, Science, English, and History) whether their grades since sixth grade had been "mostly A's (90-100)," "mostly B's (80-89)," "mostly C's (70-79)," "mostly D's (60-69)," or "mostly below D (below 60)." Similarly, in the first follow-up year, students were asked to report for each subject whether their grades from ninth grade until now were "mostly A's," "about half A's and half B's," "mostly B's," "about half B's and half C's," "mostly C's," "about half C's and half D's," "mostly D's," or "mostly below D." These responses were converted to the average of the corresponding grade point values on a 4.0 scale, where 1.0 corresponds to D, 2.0 corresponds to C, 3.0 corresponds to B, and 4.0 corresponds to A. These grade values were used to compute a student's percentile rank within each class.

Test Scores

The dataset contains test scores for each student from Math, Science, English, and History for each year. We construct a test score control that is the mean of the test scores from the two subjects for which there are teacher reports in the baseline year and first follow-up year. We also construct its square and use both as controls in our estimates.

B.3 Embedding the Roy Model in a Social Multiplier Framework

In this subsection, we cast our Roy model of social interaction into a general model of social interactions. Let there be a continuum of agents with unit mass. Every agent is endowed with one unit of (non-transferable) time. In the canonical model of social multipliers (see Becker and Murphy 2000, for example), agents derive utility from two different kinds of activities, social and asocial. Our principal departure from the usual framework is that we assume that there are two activities in which agents can engage with their peers: studying or mischief. These activities are exclusive and undertaken by separate social groups in one of two sectors: 'nerds' and 'troublemakers'. The utility derived from participating in a social activity depends on the total effective labor supplied *to that sector only*, L_j indexed by $j \in \{N, T\}$, as well as another input we label 'capital', K_j. We allow capital to broadly represent any non-human input into groups' production (e.g., school quality, diligence of adult supervision, etc.).

Agents are heterogenous along two dimensions. Their varying size and strength yield differences in the ability to cause trouble, whereas heterogeneity in cognitive ability implies differences in their ability to be a true nerd. Let the continuous function $\sigma_N(i) : [0,1] \to \mathbb{R}_+$ denote the effective units of 'nerdiness' that agent i is capable of contributing to the group (e.g., expertise in differential geometry). Analogously, agent i's troublemaking ability is given by $\sigma_T(i) : [0,1] \to \mathbb{R}_+$.

To emphasize the importance of social activity selection in the estimation of peer effects, we model the effective utility from time spent with nerds or troublemakers as perfect substitutes

$$s(i) = t_N(i)\sigma_N(i)w_N(L_N, K_N) + t_T(i)\sigma_T(i)w_T(L_T, K_T) \tag{B.1}$$

We can then nest utility from social activities in a quasiconcave utility function that depends on an individual's social 'production' $s(i)$ as defined in (B.1), asocial activities $t_a(i)$, and atomistic agents take aggregate labor and capital conditions $(\mathbf{L}, \mathbf{K})$ as given.

$$U(i) = U(t_a(i), s(i); \mathbf{L}, \mathbf{K}) \tag{B.2}$$

$$\text{s.t. } t_a(i) + t_N(i) + t_T(i) = 1$$

With this formulation, we think of the marginal return to spending an additional effective unit of time with a social group as a 'wage' that is determined by aggregate social market conditions. In the absence of a second activity, this is the standard framework for analyzing social interactions. The 'social multiplier' is generated the assumption that $\frac{\partial w_j}{\partial L_j} > 0$.[1]

[1]To see this, suppose studying were the only social activity, and we were interested in the effect of additional school resources K_N on effective time spent studying $L_N = \int_0^1 \sigma_N(i) t_N[i, w(L_N, K_N)]$. Taking the total derivative,

$$dL_N = [\frac{\partial w_N}{\partial L_N} dL_N + \frac{\partial w_N}{\partial K_N} dK_N] \int_0^1 \sigma_N(i) \frac{\partial t_N(i)}{\partial w_N} di$$

$$\frac{dL_N}{dK_N} = \frac{\frac{\partial w_N}{\partial K_N} \int_0^1 \sigma_N(i) \frac{\partial t_N(i)}{\partial w_N} di}{1 - \frac{\partial w_N}{\partial L_N} \int_0^1 \sigma_N(i) \frac{\partial t_N(i)}{\partial w_N} di}$$

With perfect substitutability between social activities, utility maximization implies a simple cutoff rule that separates individuals between social sectors in a manner analogous to a classical Roy (1951) model. Let $\sigma(i) \equiv \frac{\sigma_N(i)}{\sigma_T(i)}$ denote agent i's skill as a nerd relative to that as a troublemaker, and order agents such that $\sigma'(i) \geq 0$. Equilibrium 'labor supply' is determined by the set of agents whose comparative advantage determines the sector of their social activity, and the marginal rate of substitution between social and asocial activities. Utility maximization implies the first order condition of B.2

$$\frac{U_a}{U_j} = \sigma_j(i) w_j(L_j, K_j) \tag{B.3}$$

Diminishing marginal utility implies that more skilled agents are more socially active within their respective sector as their opportunity cost of asocial activity is higher. The agent indifferent between the two sectors, i^*(not necessarily unique, see below) has a skill ratio of

$$\sigma(i^*) = \frac{w_T(L_T, K_T)}{w_N(L_N, K_N)}. \tag{B.4}$$

For any given equilibrium wage ratio, all individuals with index $i \geq i^*$ join forces with the nerds, and individuals with $i < i^*$ become troublemakers. In our price theory of social interactions, comparative (rather than absolute) advantage determines an individual's choice of sector. Total effective labor supply to each sector is determined by

$$L_N^* = \int_{i^*}^{1} \sigma_N(s)\, t_N[s, w_N(L_N^*, K_N)] ds \tag{B.5}$$

$$L_T^* = \int_{0}^{i^*} \sigma_T(s)\, t_T[s, w_T(L_T^*, K_T)] ds. \tag{B.6}$$

Equations (B.5) and (B.6) characterize the supply side in the market for peers. A labor demand schedule with respect to i^* can be characterized as a curve that traces the marginal return per unit of effective time as the measure of the sector increases–taking the labor supply decisions of inframarginal agents into consideration. The relationship between total labor supply in the troublemaking sector and the position of the marginal agent is derived by taking the derivative of

While the numerator measures the average direct effect of the additional resources on time spent studying, when $\frac{\partial w_N}{\partial L_N} > 0$, this amount is amplified by the additional increase in the return to studying induced by the 'social multiplier': $\frac{\partial w_N}{\partial L_N} \int_0^1 \sigma_N(i) \frac{\partial t_N(i)}{\partial w_N} di$.

B.6 with respect to i^*

$$\frac{\partial L_T^*}{\partial i^*} = \sigma_T\left(i^*\right) t_T[i^*, w_T(L_T^*, K_T)] + \frac{\partial w_T}{\partial L_T^*}\frac{\partial L_T^*}{\partial i^*}\int_0^{i^*} \sigma_T\left(s\right) \frac{\partial t^*[s, w_T(L_T^*, K_T)]}{w_T} ds$$
$$= \frac{\sigma_T\left(i^*\right) t_T[i^*, w_T(L_T^*, K_T)]}{1 - \frac{\partial w_T}{\partial L_T^*}\int_0^{i^*} \sigma_T\left(s\right) \frac{\partial t^*[s, w_T(L_T^*, K_T)]}{w_T} ds} \tag{B.7}$$

The expression for the nerd sector is identical, but with a negative numerator to account for the opposite effect moving i^* has on the measure of the group. The numerator is the mechanical effect of adding a new member to the sector, and the denominator accounts for the labor supply adjustment of inframarginal members in response to the change in group size. $\frac{\partial t^*[s, w_T(L_T^*, K_T)]}{w_T}$ is always positive by the first order condition (B.3). While effective labor supply always increases with the measure of the sector, whether the mechanical effect is dampened or amplified depends on whether the social wage increases or decreases with effective labor in the sector. We turn to each case in turn.

Diminishing Marginal Social Product of Labor in Both Sectors

In contrast with the 'social multiplier' approach in which it is assumed $\frac{\partial w_j}{\partial L_j} > 0$, we begin with the assumption that additional labor supply in a social sector reduces the marginal product of participation, $\frac{\partial w_j}{\partial L_j} < 0$–a common assumption for the theory of the firm. In our setting this would correspond to a game–of math problems or bullying, for example–becoming less fun as the activity has to be shared with more participants.[2] As part of our analysis we introduce the 'relative labor demand curve', $\delta\left(i\right) : [0, 1] \rightarrow \mathbb{R}_+$, a schedule that traces the relative marginal return of a unit of effective labor in social activity when index i is the marginal agent between sectors

$$\delta\left(i\right) \equiv \frac{w_T(L_T(i), K_T)}{w_N(L_N(i), K_N)} \tag{B.8}$$

The assumption of diminishing marginal product in both sectors guarantees that the relative labor demand curve will be (weakly) downward sloping, as increasing the measure of the troublemaking sector with lower the numerator, which raising the denominator of (B.8).

[2]This holds for effective units, regardless of the number of participants. A brilliant student answering all of the questions or a talented athlete hogging the ball is an example of many effective units concentrated in a single person diminishing the social utility of participation for others.

Increasing Marginal Social Product of Labor in Both Sectors

As discussed above, the assumption that $\frac{\partial w_j}{\partial L_j} > 0$ in a single social sector has been the focus of much of the work on social interactions. Study groups allow students to benefit from division of labor on a lab project, and ensure individual students do not waste time stuck on a question to which someone else in the group knows the answer. More troublemakers at a school can divert teachers' attention and thereby reduce others' probability of punishment. We now consider the nature of equilibria when there are two social sectors characterized by increasing marginal product.

Equation B.7 shows that when $\frac{\partial w_j}{\partial L_j} > 0$, the mechanical increase in labor supply from increasing i^* is amplified by an increased labor supply from inframarginal agents due to the increased marginal product of making trouble. Conversely, the accompanying decrease in labor in the nerd sector yields an amplified decrease in the return to being a nerd. The relative demand schedule is therefore upward sloping. This creates the potential for multiple equilibria along the lines of Becker (1991) and DiPasquale and Glaeser (1998).